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Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. K. Sijtsma, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Portrettenzaal van de Universiteit op vrijdag 6 december 2019 om 10.00 uur door

Pascal Patrik Böni

geboren op 2 oktober 1967 te Basel, Zwitserland.

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Promotiecommissie:	Prof. dr. J.J.A.G. Driessen
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"It does not matter how slowly you go as long as you do not stop."
Confucius

PASCAL PATRIK BÖNI

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Contents

CHAPTER I

Restrictive Covenants and the Pricing of Private and Public Placement Bonds

Pascal Böni[1], Philip Joos[2], Frans de Roon[3]

Abstract

Using a sample of 1,217 US dollar denominated private and public placement bonds issued by European firms in the period 2002-2015, we find that the spread on private placements is on average more than 100 basis points higher than for public placements. Firms issuing private debt appear to do this in times of higher uncertainty about future economic events, seeking an option for flexible debt restructuring ex post. These firms pay excess spreads partially explained by credit risk but equally important by the use of covenants. These are used to warrant the potential re-allocation of control rights to bondholders in times of adverse contingencies. Together with credit risk, covenants also explain an important part of the variation in spreads of public placement bonds. We provide evidence of a U-shape effect of covenant intensity on spread. Differentiating between investment and financing covenants, the data suggests that the use of investment covenants resolves moral hazard problems, resulting in lower spreads. In contrast, financing covenants are used to facilitate debt renegotiation, resulting in higher ex ante spreads as investors request a compensation for contracting under higher uncertainty.

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1 Introduction

A substantial literature exists on the structure and pricing determinants of public debt. Prior literature suggests looking beyond the pure credit risk viewpoint when searching for the determinants of credit spread (e.g. Collin-Dufresne et al., 2001) and include a liquidity premium (Chen et al. , 2007; Longstaff, 2004; Longstaff et al., 2005; de Jong & Driessen, 2012) or other factors, such as macroeconomic and financial variables (Chen, 2010) or tax (Elton, 2001). Typically, these studies cannot, however, find any set of variables that can explain credit spread with high accuracy and rest with the wisdom of Jones et al. (1984) that credit models only inaccurately predict spread. Extensive tests of corporate bond pricing are predominantly concerned with models that attempt to estimate the spread more precisely (e.g., Eom et al. (2004). More recently, the interdependence of leverage and investment decisions (Kuehn & Schmid, 2014) or ownership heterogeneity (Huang & Petkevich, 2016) and their impact on spread have been researched. Although these studies have contributed importantly to our understanding of credit spreads, the use of covenants has largely been ignored in almost all modelling of bond spreads.

The use of covenants, however, may be important when pricing bond issues. On the one side, the use of covenants may mitigate agency conflicts between debtholders and shareholders. The same basic adverse selection argument that is used by Myers and Majluf (1984) for equity issues can be employed: To the extent that debt involves default risk, managers may have an incentive to borrow when their private information about the state of the firm suggests that markets will price a bond issue at a relatively favorable spread. Moreover, the severity of potential debtholder-shareholder agency conflicts may also affect bond pricing. We thus build on the work of Jensen and Meckling (1976) and Smith and Warner (1979) and test what we refer to as the moral hazard hypothesis. On the other side, incomplete contracting theory suggests that agency conflicts can be mitigated by the allocation of state-contingent control rights: management is rewarded with continued control if it honors existing debt contracts and makes the respective payments, whereas it is punished with loss of control otherwise (Aghion & Bolton, 1992). Restrictive covenants are typically used to warrant the potential re-allocation of control rights to bondholders and mitigate debtholder-shareholder agency conflicts. We build on the work of Aghion and Bolton (1992) and test what we refer to as the debt renegotiation hypothesis.

We study the pricing of both public and private debt issues, which have relatively low and relatively high agency costs respectively. Since the relative market share of private placement bonds in terms of total issue volume of primary corporate bonds, has more than doubled from 14% in 2008 to 30% in 2015[4], sufficient number of observations to compare those two channels of placing bonds are provided nowadays. The two groups of bond placements are of interest because they represent two ends of the Smith and Warner's (1979) spectrum of controlling the conflict between bondholders and shareholders: Private placement bond issuers experience more information asymmetries and higher agency costs than public placement issuers (Krishnaswami et al., 1999; Cantillo & Wright, 2000). As a result, covenants in private placement bonds are found to be more restrictive compared those in public placement bonds (Kwan & Carleton, 2010).

Previous studies suggest that private and public debt are priced differently (Blackwell & Kidwell, 1998; Fenn, 2000; Chaplinsky & Ramchand, 2004; Kwan & Carleton, 2010). In explaining the difference, various studies follow a transaction cost approach (Blackwell & Kidwell, 1998), an information asymmetry approach (Fenn, 2000) or an issuer quality approach (Chaplinsky & Ramchand, 2004; Kwan & Carleton). However, studies that test the effect of covenants on yield spreads are sparse (Reisel, 2014) and, to the best of our knowledge, do not make the distinction between privately and publicly placed bonds. The purpose of this paper is twofold. First, we aim to provide a comprehensive analysis of the pricing differences of 690 private placement bonds relative to 527 public placement bonds, issued by 310 different European firms in the years 2002 to 2015. Second, we explore whether those pricing differences can be explained by the use of covenants.

[4] Böni & Rietmann (2016)

We focus on European issuers as their placement volume of PPBs has increased substantially in recent years. In percent of total issue volumes of primarily corporate debentures in European developed markets, PPBs increased their relative market share of approximately 10% in 2005 to almost 30% in 2015.[5] Simultaneously, the annual private debt fundraising for European-focused funds, according to Preqin (2019), has grown almost eightfold between 2007 and 2018 and reached a level of approximately USD 60 billions in 2018. Although still larger in absolute terms, US focused funds only quadrupled annual private debt fundraising volumes over the same period, collecting approximately USD 94 billion from investors in 2018. These numbers illustrate the trend towards a less bank reliant economy[6] in the euro area and lend strong support to researching European issuers in more depth.

We analyze which factors determine the spread to the risk free government bond rate and whether there is a difference in spread between public and private bonds[7], i.e., the excess spread. We evaluate whether part of those pricing differences can be explained by the use of covenants and do this in three ways. First, we use covenant intensity, the number of restrictive covenants used in each bond issue. Second, we introduce an investment and a financing covenant factor derived from a factor analysis of covenants. Third, we test the relationship between spread and covenants individually, using dummy variables.

On average, we find an excess spread for private bonds that is 116 basis points higher than that for public placement bonds. However, the average credit risk of firms issuing private bonds is also one notch higher than for public bonds and relative to public bonds, private bonds are issued by smaller and younger firms, with slightly higher leverage, and with more covenants

[5] Volumes retrieved from S&P Capital IQ

[6] Today, bank lending accounts for around 55% of debt financing of euro area firms. In the United States, firms source around 70% of their debt financing directly from non-banks, and only 30% from banks. See Benoît Coeuré's (2019) remarks at the International Swaps and Derivatives Association in Frankfurt, retrievable from https://www.bis.org/review/r190627h.pdf .

[7] Throughout this paper we will use the terminology "private placement bonds", "private placements", and "private bonds" interchangeably, and likewise for "public placement bonds", "public placements", and "public bonds".

attached to them. Controlling for credit risk, we still find a significant 46 basis points excess spread of private over public bonds.

We use a binary choice model to better understand why firms would accept this difference in the cost of debt. Analyzing switchers, that is firms that use both private and public debt markets, we find that firms place bonds privately in times of higher uncertainty about future economic events. In such times, firms may issue private debt as it provides an option for flexible renegotiation ex post (Detragiache, 1994; Roberts & Sufi, 2009). Private debt providers appear to be more flexible in reorganizing debt (Bolton & Freixas, 2000; Cantillo & Wright, 2000; Chemmanur & Fulghieri, 1994), thereby avoiding premature and costly liquidation often observed with public debt. Incomplete contracting theory suggests that not all agency conflicts can be resolved through ex ante contracting. It therefore matters who controls potential agency conflicts when adverse contingencies occur. According to Aghion and Bolton (1992) this is best done by the allocation of state-contingent control rights, i.e. the use of covenants. The results of this binary choice analysis provides some support for the debt renegotiation hypothesis.

Next, we hypothesize that the use of covenants is priced in private bonds ex ante and test this prediction empirically using OLS regressions and factor analysis. Our regression results show that credit risk variables explain about 50% of the variation in spreads. Liquidity variables and market condition variables each help in further explaining the variation in spreads, but do not explain the level difference in spread between private and public bonds. Adding additional variables that typically control for information asymmetries, such as firm age or the involvement of a top tier arranger, the results remain largely unchanged. It is only when we add covenant intensity - i.e., the number of covenants attached to a bond - and its squared value in the analysis, that the difference in spread becomes insignificant, both statistically and economically. Moreover, the use of covenants appears to have as much additional explanatory power as liquidity and market condition variables together.

We find that credit risk, liquidity, market conditions, covenant intensity, and control variables jointly explain about 70% of the variation in spreads, and that the difference in spread between private and public bonds is approximately equally driven by credit risk and covenant intensity. The effect of covenant intensity on spread is non-linear, with the first number of covenants lowering the spread, whereas a high number of covenants increases the spreads again. In our regression model, the effect of covenant use on the spread ranges between -96 and +305 basis points, implying that the effect of covenant use, is in the order of magnitude of 400 basis points. To compare: in the regression model the difference between the highest and lowest rating score implies a spread of 465 basis points.

Next, we extract an investment and a financing covenant factor from factor analysis and a conditional frequency analysis. The investment factor consists of covenants that mainly limit the firm in making investments and divestments (selling its assets). The second factor is a financing factor and consists of covenants that prevent a firm from obtaining additional debt and making cash distributions to shareholders and junior debt. The investment factor lowers the spread by resolving agency problems between shareholders and bondholders. The financing factor increases the spread as these covenants limit the firm in making positive NPV investment for which additional financing is needed and optimizing its capital structure. These opposing effects and our finding that, if present, investment factor covenants are included first, followed by financing factor covenants, explain why the effect of covenant intensity on the spread is non-linear, leading to a U-shaped pattern.

In an additional analysis, we use covenants individually as dummy variables: all financing covenants show the expected sign. Attaching a limit of indebtedness covenant to a bond increases bond spread by a significant 80 basis points in the cross section. Also, we find that firms issuing private bonds are more restricted in financing activities but less restricted in investment activities than those issuing public bonds. It appears that financing covenants do in fact play an important role in explaining spreads, but also the excess spread of private versus public bonds.

These results are robust in a number of directions. First, we allow for interaction effects between the type of placement (private versus public) and the different variables that explain the spread, which does not change our findings. We employ two-stage least squares to account for potential simultaneity concerns regarding the determination of covenant use and spread, and cannot reject the hypothesis that the use of covenants is exogenous. To test whether other contract terms are likely to be subject to simultaneity, we rerun the regressions excluding potential endogenous variables, leaving the results unaltered. We use alternative proxies for various variables and include additional control variables, which does not affect our conclusions either.

Finally, we conduct an out-of-sample test to evaluate the ability of our empirical model to fit market prices. As in Eom et al. (2004) we consider the error in predicted spread to be the most informative measure of model performance. We use a sample of 1,855 Euro denominated publicly placed corporate bonds, issued in the same sample period and using the same sample restrictions. On average, our model yields a prediction error of 11 basis points. Excluding the covenant variables from the model, the prediction error increases to almost 47 basis points. The out-of-sample R^2 of the model is 29% and the correlation between the out-of-sample excess spreads and predicted spreads is 0.56. The model slightly under-predicts bond spreads by a mere 4.7%, on average, much lower than the models analyzed by Eom et al. (2004)[8] for which they find predictions between -53% and 270%, with the lowest prediction error rendering an under-prediction of -6.6% and the second best prediction error rendering an over-prediction of 43%.

Our contribution to the literature is manifold. First, we show that variables that are known to be important in explaining the spreads on public bonds are also important to explain the spread on private bonds but do not fully explain the excess spreads of private over public bonds. Credit risk variables (e.g. Longstaff & Schwarz, 1995; Collin-Dufresne et al., 2001; Huang & Huang, 2012), liquidity variables (e.g. Chen et al., 2007; Covitz & Downing, 2007; de Jong & Driessen, 2012) and market conditions (e.g. Chen 2010; Jankowitsch 2014) explain approximately 55% of the variation in spread but leave a significant excess spread unexplained. The use of covenants (e.g. Kwan &

[8] Eom et al. (2004) analyze the models of Merton (1974), Geske (1977), Longstaff and Schwartz (1995), Leland an Toft (1996), and Collin-Dufresne and Goldstein (2001).

Carleton, 2010; Christensen & Nikolaev, 2012) explains the remaining difference in excess spread entirely and increases the model fit substantially to an approximate 70%.

Second, we show that the effect of covenant use is twofold: first, as in previous studies (Cantillo and Wright, 2000; Denis & Mihov, 2003; Christensen & Nikolaev, 2012; Reisel, 2014) we find that the use of covenants can lower the spread by resolving agency problems between shareholders and bondholders. This is reflected by the use of covenants that represent our investment factor. This spread lowering effect provides support for our moral hazard hypothesis. However, our new finding is that the use of additional covenants, reflecting our financing factor, increases the spread again. We find evidence that the spread increasing effect can be as substantial or even larger than the spread decreasing effect related to the use of covenants. This observation provides support for our debt renegotiation hypothesis.

Third, we show that the effect of covenant use on the spread is as important as credit risk and that including agency costs in asset pricing models may substantially improve their explanatory power.

Fourth, we show that firms issuing private bonds are more restricted in financing activities but less restricted in investment activities than those issuing public bonds.

Finally and importantly, we provide a new explanation for the excess spread of private over public bonds to the literature, which was so far focused on transaction costs, issuer quality or information asymmetry. We provide new evidence that the use of covenants do not only mitigate problems related to information asymmetry and therefore reduce spread, but that investors may consciously accept increased monitoring and renegotiation efforts when contracting for private debt under higher uncertainty and request compensation for these efforts. Leaning on incomplete contracting theory, or results suggest that firms may prefer private debt markets as they seek the benefits of flexible debt renegotiation at the expense of additional debt limitations.

The remainder of the paper is structured as follows. Section 2 describes the data, variables, and summary statistics. Section 3 reports the results on the binary choice model, followed by our cross-sectional analysis of spreads of private placement bonds and public placement bonds and the difference in their pricing in Section 4. Section 5 provides further analysis and a series of robustness tests, and Section 6 concludes the paper.

2 Data, Variable Construction, and Summary Statistics

2.1 Data

We collect data on public and private bond issues from issuers domiciled in Europe, meaning that the ultimate parent company is domiciled in Europe. Our primary bond data are from S&P Capital IQ (S&P). Our sample period starts in 2002, as S&P rating scores are available from 2002 onwards, and ends in 2015. This sample period includes complete business cycles as well as the Global Financial Crisis in 2008 followed by the European Debt Crisis.

Our initial sample consists of 11,037 public debt issues and 1,340 private debt issues. Following previous literature, we eliminate issues by financial firms, issues with maturities shorter than one year, or longer than 30 years, and issues in currencies other than USD. This results in a final sample of 1,217 corporate bond issues by 310 firms, 527 of which are public debt issues and 690 are private debt issues. For some bond issues a package of securities is offered. These packages often differ in contract terms (e.g. maturity and covenants) and issue dates. Therefore, as in Kwan & Carleton (2010), each security is treated as a different issue.

As the S&P database might not be complete for the private debt issues, we cross-check the private debt issues for 2015 with the Bloomberg database. There are 24 private debt issues in the Bloomberg database that are not available in the S&P database. However, for 18 of these issues no additional information is available in the Bloomberg database, leaving us with only 6 issues that are not covered by S&P. Relative to the 89 issues that are covered by S&P we conclude the S&P database to be representative for the population covered by both data providers.

2.2 Variable Construction

Our aim is to analyze the pricing of private and public placement bonds and the difference in (credit) spreads between them. Spread is the difference between the yield on a corporate (fixed coupon) bond at issue and the yield on a riskless maturity-matched government bond on the same issue date. US government Treasury yields are from the Federal Reserve, which publishes constant maturity Treasury rates for a range of maturities. Treasury yields are matched to the corporate debt maturities using linear interpolation.

We use a comprehensive set of variables to explain the credit spreads of public and private placement bonds, and their difference. Based on a linear regression model, Collin-Dufresne et al. (2001) and Campbell & Taksler (2003) use proxies for credit risk and market conditions, as well as control variables to explain variation in credit spreads. As in these studies, we also use proxies for credit risk and market conditions, but also add proxies for liquidity and the use of covenants. Next to these four categories, we also use firm and issue specific control variables. Appendix A provides an overview of the variable definitions.

Credit risk

A commonly used proxy for credit risk is the credit rating of a bond or a firm (e.g. Collin-Dufresne et al., 2001; Campbell & Taksler, 2003; Longstaff et al., 2005). Since credit ratings are not available for private debt, we calculate the rating score using credit model 2.6 of S&P Global Market Intelligence (see Appendix B for details). The rating score is calculated using the most recent financial data of the firm preceding the debt issue. The model generates a letter grade score from AAA (with numerical value 1) to CCC or lower (with numerical value 18), representing a company's standalone credit risk.[9] Since bond prices are strongly affected by short-term

[9] Rating score is an ordinal variable with values ranging from 1 to 18. Ordinal variables are often used as continuous variables without harm to the analysis when applying five or more categories (Johnson & Creech, 1983; Norman, 2010; Sullivan & Artino, 2013; Zumbo & Zimmerman, 1993). We analyze the linearity assumption and estimate fitted values from a linear and a polynomial estimation, the values being approximately identical over the whole range of rating scores. The polynomial estimation only deviates from the linear estimation at the extremes (rating scores below values of 4 and larger than 15). These scores are equivalent to very good, that is AA- or better, and very bad, that is B- or worse, rating scores. The frequency of those firms in the sample is very low. For example, only 5 firms with very good and 7 firms with very bad

earnings information (Callen et al., 2017), this rating score is likely to be a better indicator than an agency's credit rating. The advantage of using this model score is that it is based on recent financial data and measures the financial condition of a bond issuer, whereas traditional ratings measure the creditworthiness of a corporation over long investment horizons (Alp, 2013) and tend to be updated slowly (Cornaggia & Cornaggia, 2013). In addition to the rating score, and motivated by the Merton (1974) model, we use as an additional proxy to measure credit risk and use book leverage, calculated as the ratio of total long-term debt to total assets of the issuer.

Market conditions

We use a number of different variables to measure market conditions. As shown by Hale and Santos (2008), firms time their bond issues to avoid recessionary periods and take advantage of favorable market conditions. To capture ups and downs in economic cycles we follow Alp (2013) and use real GDP growth rates[10] for a period of 360 calendar days prior to the bond issue.

Next, as in Chen et al. (2007) and Campbell & Taksler (2003), we use the risk-free rate of the benchmark bond and the difference between the 10-year and 2-year Treasury rates to account for the level and the slope of the yield curve. As in Collin-Dufresne et al. (2001), we interpret "slope" as an indicator of the overall state of the economy: a positive change in slope indicates bond investors are expecting higher economic growth, higher inflation and future interest rate increases. Likewise, a decrease in slope may imply a weakening economy. From this perspective and following David (2008), in our models a high level of slope is a proxy for investors' assessed risk of the economy shifting to a low-growth state.

ratings that place bonds privately are in the overall sample. To control for potential effects from the rating score being an ordinal variable, we re-run the regressions presented later in this paper and restrict the sample to firms with rating scores higher or equal to 4 and lower or equal to 15, the results do not change in any material way.

[10] We use European GDP data from Eurostat (http://ec.europa.eu/eurostat/web/nationalaccounts/data/main-tables adjusted for inflation given by the Harmonised Index of Consumer Prices (HICP) oft he Euro area compiled by Eurostat and the national statistical institutes. Details can be retrieved from http://ec.europa.eu/eurostat/web/hicp/data/database.

Merton (1974) predicts that equity volatility impacts the likelihood of reaching boundary conditions for default. Campbell & Taksler (2003) find that an increase in equity market volatility increases credit spreads. To capture changes in aggregate equity market volatility, we use the CBOE VIX-index values, which are a weighted average of eight implied volatilities of near-the-money options on the OEX (S&P 100–Index).

As in Acharya et al. (2007), we measure whether an industry is distressed by the return of the index representing the issuer's industry. Following Cremers et al. (2008), we calculate the index return over the past 180 days prior to a bond issue. We use the MSCI Europe Index family and its industry specific derivatives to calculate this 180 day return prior to a bond issue. We also use Europe wide total stock market returns.

Following Fenn (2000) and Chaplinsky and Ramchand (2004), we include a time index dummy variable ("time"), equal to 0 in 2002 and increasing by 1 every year thereafter to control for potential structural changes over time. Alp (2013) studies the time-series variation in corporate credit rating standards from 1985 to 2007, and finds that rating standards are subject to structural shifts, with investment-grade standards tightening and sub-investment-grade standards loosening in the same period. We therefore also interact the time index with the proxy for rating.

Finally, We use the Rule of Law score as developed by Kaufmann et al. (2010)[11] and used in Brown (2016) to proxy for the quality of the enforcement environment of an issuer. Higher scores equate to a higher quality of enforcement environment.

Liquidity

Previous literature has shown that corporate bond spreads can partially be explained by liquidity factors (e.g., Longstaff et al., 2005; Chen et al., 2007; Covitz & Downing, 2007, de Jong &

[11] Rule of Law is one of six dimensions measured within the Worldwide Governance Indicators project of the World Bank, covering 200 countries since 1996. The six governance indicators are based on different data sources including commercial business information providers, public sector data providers as well as non-governmental organization data providers and survey providers. A more comprehensive description is available on www.govindicators.org.

Driessen, 2012). We use three measures of liquidity in our analysis to explain the difference in spreads between public and private bonds.

The first measure for liquidity is the log issue amount, which aims to gauge the bond specific liquidity. The second measure is the liquidity premium obtained from decomposing sovereign bond yields into a credit and liquidity component (e.g., Longstaff, 2004; Ejsing et al., 2012; Helwege et al., 2014). Here a liquidity premium is obtained by comparing pairs of bonds with the same credit risk but with different liquidity. We use Refcorp (Resolution Funding Corporation) bonds, which are fully collateralized by Treasury bonds and guaranteed by the US Treasury. The yield on these Refcorp bonds compared to the more liquid, but with the same credit risk, US government benchmark rate gives an estimate of bond market liquidity. We use a 90-day moving average of the spread between the 7-year Refcorp bond-yield and the respective government bond benchmark rate for each issue date as a liquidity measure.

The third liquidity measure is the Pástor & Stambaugh's (2003) stock market liquidity measure. As shown by e.g., Lin et al. (2011), de Jong & Driessen (2012), and Acharya et al. (2013), expected corporate bond returns are strongly affected not only by bond market liquidity, but also by stock market liquidity.

Covenant use

"Agency costs are as real as any other costs" (Jensen & Meckling, 1976, p.357). They are based on information asymmetry between borrower and lender and typically mitigated by the use of covenants. However, covenant use is rarely used in explaining bond spreads. As in Bradley & Roberts (2015), Hollander & Verriest (2016), and Demerjian (2017) e.g., we use covenant intensity, which is the number of covenants (ranging from 1 to 18) to measure the effect of covenant use. To allow for the possibility that the effect of covenant intensity may be non-linear as in Reisel (2014), or because of diminishing marginal effects of additional covenants on the spread, we use both covenant intensity as well as its squared value in our regression model. In addition, to reduce the dimensions of the 18 covenants, we will also use factor analysis to replace the covenant intensity by a limited number of factors that may possibly summarize the information in the covenants. Appendix C provides an overview of the 18 debt covenants.

Information asymmetry problems are also mitigated by financial intermediaries, such as banks involved in a bond placement. We use a dummy variable indicating whether the bond issue was placed by a top tier arranger (as in McCahery & Schwienbacher, 2010). A bank is classified as a top tier arranger when it was one of the three biggest players in terms of market share in the year preceding the debt issue. Data on market share for total annual placements in the European bond market are obtained from Bloomberg.

Based on the reputation building theory of Diamond (1984), we use the log age of the firm to additionally control for information asymmetry effects. In line with James and Wier (1990), Berger and Udell (1995) and Krishnaswami et al. (1999) we expect younger firms with limited financial histories to have a greater degree of information asymmetry. Age is defined as the number of years since inception.

Control Variables

We add a number of firm and issue specific control variables to the regressions. Firm size is measured by the logarithm of total assets and total revenues of the issuer. Profitability of a firm is measured by the ratio of EBIT to revenues (profit margin). To control for industry affiliation, we include industry dummy variables taking the value of one, if an issuer is affiliated to a certain sector defined by its Global Industry Classification Standard (GICS) sector code. We keep 9 out of 11 GICS sectors (we drop financials and real estate) and the benchmark sector is “industrials”. To control for effects in excess of the country enforcement environment (D. P. Miller & Reisel, 2011), we include a dummy variable for issuer domicile, with the UK being the benchmark domicile.

Finally, we control for bond maturity, and use a dummy variable indicating whether the issuer or its parent company is a listed company.

2.3 Summary Statistics

Bond characteristics, Firm characteristics, and Market Conditions

Table 1 presents summary statistics for bond and firm characteristics, as well as for the market conditions at the issue date of the debt. Summary statistics are reported separately for public and private debt issues.

Panel A shows statistics for bond specific variables. Comparing the public and private debt issues, we see that on average the spread on private bonds is 116 basis points higher than on public bonds. Average maturity and issue size are comparable for both sets of bonds, although the median maturity for private bonds is one year longer than for public bonds. Private bonds are issued with top-tier banks more often than public bonds (49% versus 39%) and have on average more covenants attached to them as well (7.4 versus 6.6). This is also witnessed by the median covenant score (9 versus 8).

Firm characteristics are described by Panel B. Here we see that firms issuing private debt are on average 9 years older than firms issuing public debt, although the median age is only one year higher. Both in terms of assets and revenues, firms issuing private debt are about one third smaller than firms issuing public debt, whereas their median size is about half of that of the firms issuing public debt. Firms issuing private debt have a bit higher average leverage and are less often listed, whereas in terms of profitability they are similar to firms issuing public debt. Finally, the average rating score of private debt issuing firms is with 9.5 about one notch below that of public debt issuing firms, which also holds for the medium rating score (9 versus 8). As this may be the reason why the average spread of private bonds is 116 basis points higher than for public bonds, we will look at the cross-sectional variation in spreads and rating scores to address this.

La2stly, Panel C shows the market conditions at play when debt is issued. Focusing on the significant differences, we see that relative to public debt, private debt is issued more often following lower GDP-growth, but also after high stock market returns for the own industry. It is also issued relatively more often when (benchmark) interest rates are lower and the yield curve is steeper, and when stock market volatility is relatively low.

Appendix Table I shows the Pearson product-moment correlation coeffcients (r) of the variables used. We find mostly weakly[12] correlated (r < 0.39) independent variables. Some few variables show moderate or strong correlations. As it is likely that some economic variables, such as for example VIX and the MSCI index return or market liquidtity are moderately to highly correlated with each other, we use the variance inflation factor (VIF) to control for potential collinearity and multicollinearity problems in our regression analysis. We use a tolerance limit to detect instances where an independent variable should not be allowed into the regression model of 10 for VIF and 0.1 for 1/VIF.

Risk-adjusted Excess Spreads

The summary statistics in Table 1 show that private debt issues on average have a higher spread, but also a higher rating score. To see whether the higher spreads are caused by higher credit risk, Table 2 shows excess spreads adjusted for rating score, based on the regression

$$spread_{it} = \beta_0 + \beta_1 rating_{it} + \varepsilon_{it}, \tag{1}$$

where $spread_{it}$ is the difference between the yield on a corporate fixed coupon bond calculated as internal rate of return (IRR) and the yield of the riskless maturity matched government bond on the issue date and $rating_{it}$ is the (numerical) rating score. $spread_{it}$ refers to issue *i* at date *t*.

Panel A of Table 2 shows the average residual ε_{it}, or risk-adjusted spread, of private placement bonds over public placement bonds, per rating category. The last two columns show the difference between the average risk-adjusted spreads for private versus public debt issues. The cross-sectional excess spread of private over public bonds amounts to 43 basis points. For 11 out of the 15 rating categories, private bonds have higher risk-adjusted spreads than public bonds, 9

[12] We tentatively label the strength of the association for absolute values of r, 0-0.19 as very weak, 0.2-0.39 as weak, 0.40-0.59 as moderate, 0.6-0.79 as strong and 0.8-1 as very strong correlation, these limits arbitrarily chosen and applied in the context of using the VIF as our main indicator for potential problems of collinearity and multicollinearity problems.

of them statistically significant so, ranging from 15 to 243 basis points. It is only for the B and B+ rated bonds that the private bonds have a marginally significantly lower average risk-adjusted spread, whereas the other categories where the risk-adjusted spread for private bonds is lower have a low number of observed bonds in either category.

Panels B and C show the average risk-adjusted spreads across different maturity groupings or industry affiliation. For all three maturity groups, private bonds have higher average risk-adjusted spreads than public bonds. Grouping bonds according the firm's industry affiliation, except for issues in the consumer discretionary GICS sector, private bonds always have higher risk-adjusted spreads than public bonds. In Appendix Table 2 we show similar results when grouping bonds according the firm’s domicile country, except for issues in the Netherlands. We thus conclude that accounting for credit risk with the rating score cannot account for the difference in spreads between private and public debt issues.

3. The Choice for Private Placement Bonds versus Public Placement Bonds

Economically, for an average private offering in the amount of USD 500 million and a cross-sectional risk-adjusted excess spread of 43 basis points by our sample, the difference in spread represents an annual cost to a firm of approximately USD 2.15 million. With an average maturity of nine years, this translates into a total cost of approximately USD 19 million. This leads to the question why firms place bonds privately instead of publicly and bear this incremental cost of debt. Prior literature offers several potential explanations. We refer to these as (1) the costly information production hypothesis, (2) the moral hazard hypothesis and (3) the debt renegotiation hypothesis.[13]

[13] An additional hypothesis offered by prior literature is the information disclosure hypothesis: Firms may not want to disclose proprietary information potentially valuable to competitors in the context of a debt placement. These firms will prefer private debt as private lenders have the ability to keep sensitive information confidential (Campbell, 1979; Bhattacharya and Ritter, 1983; Krishnaswami et al., 1999).

First, the costly information production hypothesis suggests that firms may prefer private over public debt because the cost of producing the information required for public debt financing is comparatively higher (Blackwell & Kidwell, 1988; Eugene F Fama, 1985). Consistent with the costly information production hypothesis, various papers find a positive relation between firm size and the level of public debt in a firm's balance sheet (Cantillo & Wright, 2000; Denis & Mihov, 2003; Houston & James, 1996 and Krishnaswami et al., 1999).

Second, the moral hazard hypothesis suggests that firms with risky debt need to be monitored as they might engage in actions damaging to debtholders. Based on agency theory, the main concerns may arise from information asymmetries leading to asset substitution where shareholders invest in risky projects given bounded (limited) liability but unlimited benefits (Jensen & Meckling, 1976; Galai and Masulis, 1976). Myers (1977) shows that moral hazard may lead to underinvestment problems as firms with risky debt forgo positive net present value projects when cash flows primarily flow towards debt repayments. Rational investors, in this argumentation, will ask higher returns or intensify monitoring of such borrowers.

Third, we propose the debt renegotiation hypothesis: firms may prefer private over public debt because of its flexibility to be renegotiated or restructured (Detragiache, 1994) and avoid pre-mature liquidation (Chemmanur & Fulghieri, 1994). Our debt renegotiation hypothesis is based on incomplete contracting theory (Grossman & Hart, 1986; Hart & Moore, 1988; Aghion & Bolton, 1992; and Hart & Moore, 1998) and based on the assumption that it is often impracticable to specify all relevant contingencies related to later changes in the state of the world. Parties to a debt contract then manage contingencies by the use of covenants and anticipate renegotiation in the future. Roberts & Sufi (2009), for example, show that over 90% of long-term private debt contracts are renegotiated prior to maturity (determined by changes in credit quality, investment opportunities, collaterals, macroeconomic fluctuations, equity market conditions). The renegotiation-based explanation of debt choice is built on the hypothesis that private lenders

Testing this hypothesis, however, would require observations ex post the observed bond issues and we do not test this hypothesis as this is beyond the scope of this study.

have superior ability, compared to public lenders, to decide about the liquidation or continuation of a lending relationship based on their access to private information (Rajan, 1992; Chemmanur & Fulghieri, 1994; Bolton & Freixas, 2000; Cantillo Wright, 2000) . Private lenders request more restrictive covenants used to manage events of adverse contingencies (Arena and Howe, 2009) and these covenants are expected to reduce the overall cost of debt (Smith & Warner, 1979; Reisel, 2014; Bradley & Roberts, 2015). The debt renegotiation hypothesis is also in line with more recent research: Demerjian (2017) examines the use of financial covenants when contracting for debt under uncertainty. He finds that a lack of information about future economic events and their consequences for the borrower's creditworthiness is positively related to covenant intensity. According to Nikolaev (2017), monitoring mechanisms, such as the use of covenants, are positively related to renegotiation intensity. Christensen et al. (2019) find that credit-supply frictions influence the type and strictness of covenants in debt contracts, and that financial covenants represent a channel through which economic shocks to lenders are transmitted to the nonfinancial sector. Drawing on the literature of Demerjian (2017), Nikolaev (2017) and Christensen et al. (2019), it appears plausible that debt renegotiation is costly and it is conceivable this explains the excess spread of private over public bonds.

We analyze a firm's choice for private versus public debt for our sample and to analyze whether we find support for our hypotheses above. We use logistic regressions as described in equation (2) below.

$$placement_{it} = \beta_0 + \sum_{j=1}^{K_{Credit}} \beta_{1ji} credit_{jit} + \sum_{j=1}^{K_{Liquidity}} \beta_{2ji} liquidity_{jit} + \sum_{j=1}^{K_{Market}} \beta_{3ji} market_{jit} + \sum_{j=1}^{K_{Agency}} \beta_{4ji} agency_{jit} + \sum_{j=1}^{K_{Control}} \beta_{5ji} control_{jit} + \varepsilon_{it} \qquad (2)$$

We regress the dummy variable $placement_{it}$ that is one for private placement bonds and zero for public placement bonds, on a constant and the different categories of variables discussed in Section 1.2: credit risk variables, market conditions, liquidity variables, agency cost variables, and a set of control variables. For instance, there are K_{Credit} different credit risk variables $credit_{ijt}$, $j=1..K_{Credit}$. Prior literature suggests that covenant choice is endogenous with respect to financing

(Demiroglu & James, 2010; Smith & Warner, 1979). We therefore estimate the logistic regressions without using covenant intensity to avoid a potential endogeneity bias.[14]

Table 3 shows our binary choice model. We use the odds ratio to indicate an increase (odds ratio > 1) or decrease (<1) in the odds of placing a bond privately. The percentage change in odds for a one standard deviation increase in the used variables is indicated in brackets. Column 1 of Table 2 shows the results when we include the total sample, that is all bond issues. Column 2 includes bond issues executed by firms that use private and public bonds, which we call switchers. This group is of interest as these firms access both markets and actually choose between issuing private versus public bonds. Column 3 includes bond issues by non-switchers, i.e., firms that issue either private or public bonds.

We find little evidence of a significant relation between placement choice and credit risk, as proxied by the rating score or leverage. Also, profitability appears to be of minor importance when choosing either a private or public placement. These results contrast the findings of Denis and Mihov (2003) and Kwan and Carleton (2010), who find that firms with higher credit risk, higher leverage or with less profitability borrow privately rather than using public debt sources. Quite contrary, the odds ratio indicates that a higher rating score (equal to higher credit risk) reduces the likelihood of placing a bond privately.

Turning to our three hypotheses (costly information production, moral hazard and debt renegotiation), we find no support for the costly information production hypothesis as we observe a negative relation between firm size and the likelihood of placing debt publicly. Also, the issue amount is statistically significant in all specifications and greater than one, indicating that larger issue amounts increase the odds of placing a bond privately. The data suggests that the likelihood of placing a bond privately increases by approximately 60% for switchers and with a one standard deviation increase in issue amount. If out of pocket transaction costs were the main determinant of placing a bond privately, then the likelihood of placing a bond by this channel

[14] Using a probit model with endogenous covariates (ivprobit) and based on Wald's exogeneity test of the instrumented variables, we reject that covenant intensity is exogenous with $p = 0.04$ ($p = 0.01$) for specifications one (two).

would decrease with an increase in issue amount. This observation contrasts again Kwan and Carleton (2010), who find that firms use the private market when the issue size is small. [15]

Turning to the moral hazard hypothesis, for firms that use both placement channels (switchers in column 2), the odds of placing a bond privately is two times higher when a top-tier bank is involved. Our alternative measure for agency costs, firm age, is significant in columns (1) and (3) but not for switchers as indicated in column (2).

Turning to the debt renegotiation hypothesis, the level and the slope of the yield curve both affect the likelihood of placing a bond privately. An increase in the risk-free rate or a steepening of the slope increase the odds of placing bonds privately for switchers. Conversely, an increase in equity volatility (VIX) makes it less likely that a firm places bonds privately. Also, favorable industry conditions as measured by the index return and a higher quality enforcement environment as proxied by the rule of law score appear to reduce the odds of placing a bond privately.

A number of interpretations can be drawn from these findings:

First, firms appear to place bonds privately when the yield curve slope is steep and the risk-free rate high. A steep slope is an indicator of the state of the business cycle (Collin-Dufresne et al., 2001) pointing towards strong business activity (Eugene F. Fama, 1986). This can be seen as a proxy for investors' assessed risk of the economy shifting to a lower growth state in the future (David, 2008). Second, higher risk-free rates might make a firm more prone to default and less likely to tap credit markets directly (Cantillo and Wright, 2000), increasing the likelihood of using a private placement. Third, the odds ratios observed for industry conditions and the quality enforcement environment reveal additional information on debt choice: The likelihood for

[15] Also, Blackwell and Kidwell (1988) find a difference in flotation costs between private and public placement bonds in the magnitude of 32 basis points. These flotation costs consist of the underwriter's compensation and out-of-pocket expenses for issuing a bond. They are expensed at or around the bond issue time, therefore being one-time costs. The risk-adjusted excess spread of private over public placement bonds amounts to approximately 43 basis points annually (see Table 2). Considering the average bond maturity of nine years, this leads to an increase in the cost of debt of 387 basis points. It appears unreasonable to assume a rational firm would borrow at this incremental cost of debt without good reason. The costly information production hypothesis thus provides little explanation for the choice for private placements bonds.

placing a bond privately increases when industry conditions are worse and default probabilities increase (Acharya et al., 2007), and when firms are domiciled in countries with a lower quality enforcement environment. The latter affects a lender's perception of borrower risk, as it is a proxy for how strictly debt contracts can be enforced and thus correlated with the likelihood of the lender being repaid in the event of bankruptcy (Brown, 2016). These findings are consistent with the debt renegotiation hypothesis put forth earlier. In uncertain market conditions, firms may require flexibility to renegotiate or restructure debt ex post (Detragiache, 1994; Roberts & Sufi, 2009) with private lenders requesting more restrictive covenants used to manage events of adverse contingencies (Arena and Howe, 2009).

Fourth, turning to the moral hazard hypothesis, switchers that place bonds privately appear to use top tier arrangers more often. Krishnaswami et al. (1999) and Cantillo and Wright (2000), find that firms are largely driven by agency costs when choosing the private market to place capital. In line with this view, firms issuing private placement bonds appear to use a top-tier arrangers' reputation to certify the quality of a bond being placed (McCahery & Schwienbacher, 2010) and reduce costs associated with information asymmetries. Fang (2005), for example, finds that the involvement of reputable arrangers leads to pricing improvements, in particular for junk bonds, for which information asymmetries are expected to be highest. She finds that reputable arrangers are selective and apply more stringent underwriting criteria when it comes to junk bond issues. In line with Diamond's (1991) theory of bank loan demand,[16] firms issuing private placement bonds may lean on arranger reputation in circumstances in which reputation effects are important. As suggested by the moral hazard hypothesis, firms issuing risky debt might need to be monitored as they might engage in actions damaging debtholders as described in agency theory (Jensen & Meckling, 1976; Myers, 1977).

[16] Diamond (1991) analyzes the conditions under which debt contracts are monitored by lenders directly as opposed to banks that monitor moral hazard. He concludes from his theory of bank loan demand that (p. 716) "in periods of high present or anticipated future real interst rates or low present or future anticipated economywide profitability, a higher credit rating is required to borrow without monitoring, implying that the demand for bank loan monitoring is then high and that the average new bank loan goes to a safer, higher-rated customer."

Overall, the results from the binary choice model in Table 3 suggest that a firm's decision to issue a bond privately is not driven by credit risk or profitability but mainly by the issue amount and uncertain market conditions. The latter are expressed by a steep slope, a high level of the risk-free rate, worse industry conditions as measured by industry specific index returns and a lower quality enforcement environment.

4. The Cross-Section of Excess Spreads of Private Placement Bonds versus Public Placement Bonds

Both hypotheses, debt renegotiation and moral hazard, are associated with the use of restrictive covenants. Under the debt renegotiation hypothesis, debt issuers and investors manage events of adverse contingencies and avoid pre-mature or costly liquidation (Chemmanur & Fulghieri, 1994; Arena & Howe, 2009) by flexible debt renegotiation (Detragiache, 1994; Roberts & Sufi, 2009) with private lenders requesting more restrictive covenants (Arena and Howe, 2009).

Under the moral hazard hypothesis, the same basic adverse selection argument that is used by Myers and Majluf (1984) for equity can be applied to debt. To the extent that debt involves default risk, managers may have an incentive to borrow when their private information about the state of the firm suggests that markets will price a bond issue at a relatively favorable spread. Information asymmetries and especially the way potential debtholder-shareholder agency conflicts are mitigated may therefore affect bond pricing.

The use of restrictive covenants can be measured in different ways. We first use covenant intensity, which is a count of covenants attached to each bond issued, and hold that the way debt renegotiation and moral hazard are managed affect bond pricing ex ante. Smith and Warner (1979) argue that since the restrictions imposed by the use of covenants are costly to the firm, they must confer some offsetting benefit. According to them, the benefit of using covenants is the reduction in agency costs, which translates into a lower cost of debt. Consistent with this prediction, Bradley & Roberts (2015) find that the inclusion of covenants in loan contracts leads to lower yields. Reisel (2014) likewise finds that covenants reduce the cost of debt for public straight bonds, but she also finds that covenants restricting payouts and additional debt leads to a marginally significant increase in the cost of debt, indicating that the effect of covenants may be ambiguous.

We expect that the use of covenants explains some of the variation in bond spreads. To verify this assumption and to explain the cross-section of spreads on private versus public placement bonds, we use the following regression model:

$$spread_{it} = \beta_0 + \beta_{1i}placement_{it} + \sum_{j=1}^{K_{Credit}} \beta_{2ji}credit_{jit} + \sum_{j=1}^{K_{Liquidity}} \beta_{3ji}liquidity_{jit} + \sum_{j=1}^{K_{Market}} \beta_{4ji}market_{jit} + \sum_{j=1}^{K_{Agency}} \beta_{5ji}agency_{jit} + \sum_{j=1}^{K_{Control}} \beta_{6ji}control_{jit} + \varepsilon_{it}. \qquad (3)$$

Thus, we regress spread ($spread_{it}$) for issue i in year t on a constant, a dummy $placement_{it}$ that is one for private placement bonds and zero for public placement bonds, and the different categories of variables discussed in Section 1.2: credit risk variables, market conditions, liquidity variables, agency cost variables, and a set of control variables. For instance, there are K_{Credit} different credit risk variables $credit_{ijt}$, $j=1..K_{Credit}$. Equation (2) is essentially an extension of Equation (1), where we add next to credit risk the other categories of variables as well as the private placement dummy.[17]

4.1 Baseline regressions

Table 4 shows OLS-estimates of different versions of Equation (2), where in each column we set different subsets of variables to zero.

Column 1 of Table 4 shows the results when we only include credit risk variables. This specification is comparable to Equation (1), except that we also include leverage as a credit risk

[17] And note that we also add leverage as a credit risk variable.

variable. Credit risk variables (together with the private placement dummy) can explain a bit more than 50% of the cross-sectional variation in credit spreads, as witnessed by the R^2. However, the coefficient for the private placement dummy shows that private bonds have on average a 46 basis points higher spread than public bonds, which - with four standard errors - is reliably different from zero. Thus, from the average difference of 116 basis points between excess spreads on private versus public bonds reported in Table 1, credit risk variables can explain more than half of it, both in terms of cross-sectional variation and in level, but there is still a sizeable and significant difference left.

Looking at Columns 2 and 3, we see that adding either market condition variables or liquidity variables helps in explaining the cross-sectional variation in spreads by an additional five percent (the R^2's increase to 56%), but hardly affect the private placement dummy. Thus, these variables do not help in explaining the difference in spreads between private and public placement bonds.

It is only when we add covenant intensity and its squared value next to credit risk that the private placement coefficient falls to an insignificant 13 basis points, as is shown in Column (5). The R^2 increases to almost 60%, so covenant use explains as much of the cross sectional variation as the liquidity and market condition variables together. Importantly, it is indeed the combination of covenant intensity and its squared value that helps explaining the average difference in spreads, as including only covenant intensity itself, as in Column (4) of Table 4, leaves the private placement coefficient at 43 basis points and shows only a minor improvement in the R^2 relative to baseline specification in Column (2) with only credit risk variables.[18]

The lasts columns of Table 4 show that combining the four categories of variables (Column (6)) and adding control variables (Column (7)) increases the R^2 to 66% and 68% respectively and slightly lowers the private placement coefficient to about 10 basis points. Column (8) also adds industry dummies to this and shows that the full model explains more than 70% of the cross-

[18] Similarly, using hierarchical (nested) regressions in unreported tables, we find statistically significant increments in R^2 when agency costs are added to credit risk variables. These increments are larger than those observed for the addition of liquidity, market condition or control variables.

sectional variation in spreads and lowers the private placement coefficient to less than 5 basis points.

We thus conclude that, next to credit risk variables, the main driver of the difference in spreads between private and public bonds is covenant intensity and its squared value - which reduce the difference in spreads from a sizable and significant 46 basis points to an insignificant 13 basis points. Market conditions and liquidity measures, together with control variables and industry dummies all help in explaining the cross-sectional variation in spreads, but only industry dummies lower the difference in excess spreads a bit further to 5 basis points.

Interpreting the regression coefficients

Looking at the full regression model in Column (8), we see that the (partial) effect of an increase in rating score[19] increases the spread on (both public and private) bonds by about 26 basis points. Since the maximum rating score (lowest rating) is 18, this implies that differences in credit risk can explain up to 465 basis points in spread according to the regression model.

For market conditions, although stock market volatility, the benchmark yield, and GDP-growth are statistically significant different from zero, the economic effect of changes in these variables on the spreads is very minor, less than one basis point for any normal change in them.

The liquidity variables have both statistically and economically meaningful effects on the spread. For instance, two otherwise equal issues that differ in size by a factor ten, the estimated coefficient for (log) issue size implies that they would differ in spread by about 22 basis points. Although liquidity variables show up significantly and help in explaining the cross-sectional variation in spreads as witnessed by the increase in R^2 from 51% to 56%, somewhat surprisingly, the average excess spread of PPBs over PUBs appears to be unaffected by the liquidity variables. Bond pairs with the same credit risk but different liquidity should be priced differently (see, for example, Ejsing et al., 2012; Helwege et al., 2014; Longstaff, 2004). Also, privately placed bonds

[19] Recall that an increase in score is equivalent to an increase in credit risk.

are typically only traded among qualified institutional investors and subject to holding periods of six to twelve months subsequent to their issuance. After controlling for credit risk and market conditions, one could therefore expect that liquidity explains some if not all of the excess spread of private over public placement bonds. However, it appears there are other meaningful differences between private and public placements bonds beyond liquidity, i.e. covenant intensity and its squared value.

The fact that both covenant intensity and its squared value show up significantly, implies that the effect of covenant intensity on the spread is indeed non-linear, as suggested by the findings of Reisel (2014) and our conjecture that there may be marginally decreasing effects from the use of covenants. The coefficients for covenant intensity (squared) in specification (8) imply that the first covenant reduces the spread by about 30 basis points, and that the maximum decrease occurs at six covenants, which leads to a 96 basis points lower spread. The quadratic form implies that beyond six covenants, the effect on spreads start to increase, with even positive effects on the spread when there are 12 or more covenants. With a maximum number of covenants of 18, the spread would be 305 basis points higher. The variation in covenant intensity therefore can explain a difference of about 400 basis points in spread, similar in magnitude as the 465 basis points due to credit risk. In the next section we will analyze the effect of covenants on the spread in more detail.

The remaining coefficients in specification (8) that are statistically different from zero, are also economically meaningful. For instance, the coefficient for (log) age, which also proxies for agency costs, implies that a firm that is ten times older than an otherwise equal firm, would pay 39 basis points less. Similarly, for the control variables, an otherwise equal firm that is ten times bigger in terms of total assets, would have a spread that is about 42 basis points lower. Each percentage point increase in profitability lowers the spread with 1.2 basis points and being listed lowers the spread by 67 basis points. For the bond specific controls, the results imply that each additional year to maturity adds one 1.3 basis points to the spread.

4.2 The role of covenants

The results in Table 4 suggest that covenants play an important role in explaining the difference in excess spreads between private and public bonds, and that the effect of covenant intensity on spreads takes the form of a U-shape, initially lowering the spread, but then increasing it as the number of covenants goes beyond six.

Using covenant intensity only looks at the number of covenants, not whether there is a difference in economic meaning and effect between the various covenants. Table 5 shows the unconditional and conditional frequencies of the 12 most often used covenants. As the first line of Table 5 shows, the first eight covenants occur in more than 50% of the bonds, the next four in more than 25% of the bonds. The remaining six covenants, which are excluded from the table, occur in less than 25% of the bonds, four of them in even less than 10%.

To better understand the role of covenants in explaining excess spreads, we use factor analysis and see whether the variation in the covenants can be captured by a limited number of factors. The results of the factor analysis, presented in Appendix D, show that the first two factors have eigenvalues of 6.3 and 3.4 respectively, whereas the remaining factors all have eigenvalues below 1.0. The second and third row of Table 5 show the factor loadings of these two factors. As can be seen, the first eight covenants - which have the highest frequency - coincide with loadings on the first factor being higher than 0.5. Likewise, the last four covenants - with frequencies between 25% and 50% - coincide with loadings on the second factor being higher than 0.5. There is some overlap for covenants six through nine that have loadings on both factors, but they then have loadings below 0.5 for either factor.

Nikolaev (2010) categorizes (restrictive) covenants into three sub-groups: i) investment-related restrictions, ii) payout-related restrictions, and iii) financing-related restrictions. Covenants one and nine in Table 5 do not adhere to these types of restrictions, but merely indicate the presence of certain financial indicators. Apart from this, the first eight covenants in Table 5, reflecting the first factor, are a combination of investment-related and payout-related restrictions. The last four covenants, reflecting the second factor, are a combination of financing-related and one payout-related restrictions. We therefore tentatively coin the first factor as investment factor and the second as financing factor. Broadly speaking, the covenants in the investment factor limit the firm in making additional investments and selling its assets. The covenants in the financing factor limit the firm in obtaining additional debt and making distributions to shareholders or junior debt, thus preventing the firm from increasing its leverage.

The remaining part of Table 5 shows the conditional frequencies of the covenants, which further confirms the distinction in the two sets of covenants, as well as a logical ordering in them. First, excluding covenants one and nine, which are not really restrictions but indicate the presence of financial information, we see that whenever one of the investment factor covenants is present, at least in 80% of these bonds the other investment factor covenants are present as well. On the other hand, the financing factor covenants show up in less than 50% these bonds. Thus, the first eight covenants indeed reflect one largely common factor.

Next, focusing on the conditional frequencies for the financing factor covenants, we see that these are all above 85%, with the exception of covenant nine again. These are much higher than the frequencies conditional on the investment factor covenants, confirming that they also present one common factor.

Finally, except for covenant nine, whenever one of the financing factor covenants is present, in at least 92% of these bonds investment factor covenants are present as well. This suggests that there is a logical order in the covenants: first the investment factor covenants are included in the bond issue, and next - in roughly half of the issues - financing factor covenants are added to them as well.

Using the covenant factors to explain excess spreads

Having identified the investment and financing factors to capture most of the variation in the covenants, we next include them in our regression (2) to analyze their effect on the excess spreads. The last column (9) of Table 4 shows the results, which can be compared to specification

(8) in Table 4, that contains all categories of variables and controls, and uses covenant intensity and its squared value.

Using the investment and financing factors instead of covenant intensity, gives a slight improvement in explaining spreads: relative to specification (8), the R^2 increases a bit from 71% to 73%, and the difference in excess spreads between private and public bonds decreases by about one third from an insignificant 4.6 basis points to 2.9 basis points.

More importantly, the investment and financing factors both show up significantly, with the investment factor having a negative effect on spread and the financing factor a positive. The finding that the spread decreases due to the inclusion of investment factor covenants and increases due to financing factor covenants, combined with the fact that there appears to be a logical order to first include the investment factor covenants before adding financing factor covenants, is in line with the U-shaped pattern of the effect of covenant intensity on spread: Initially the investment factor leads to an increase in covenant intensity and an accompanying decrease in spread. Subsequently, the financing factor further increases covenant intensity with an accompanying increase in spread. We postpone the discussion of these results as we first aim to evaluate these findings in more detail in the next paragraph.

Using covenant dummy variables instead of covenant intensity or covenant factors

If spread is negatively (positively) related to the investment (financing) factors, then we may expect that the covenants defining these factors have a negative (positive) sign if used individually as dummy variables in an OLS regression. To test this, the covenants described in Appendix C are used as dummy variables taking the value of one if attached to a bond issue and zero otherwise. Covenants nine and fourteen turn out to be collinear in the regression analysis. Both are investment covenants. We keep covenant fourteen in the regression specification.[20] The results

[20] We also run the regression keeping covenant nine. Both covenants turn out to be insignificant. Additionally, to control for potential effects from not including covenant nine in our measure of covenant intensity or our factors, we reconstruct "covscore" and our investment and financing factor and exclude covenant nine. The regression results presented earlier do not change in material ways.

of the OLS regression using covenant dummy variables are shown in Table 6, specification (2). The expected sign for the financing covenants (number one, two, seven and seventeen) is positive, for the investment covenants (number three, six, eight, ten, eleven, fourteen and fifteen) the expected sign is negative. Specification 1 is the baseline regression as in Table 4, specification 8, used for comparison. Columns (3) and (4) show the frequency of covenants attached to private and public placements bonds respectively.

As for the financing covenants, they all show the expected sign. The distribution covenant (cov1) and the limit of indebtedness covenant (cov7) are statistically significant at the 1% level and increase spread by a substantial 64.6 and 79.7 basis points respectively if attached to a bond, on average. Turning to frequencies in columns (3) and (4), financing covenants are attached more often to private placement bonds than to their public counterparts. For example, the distribution (limit of indebtedness) covenant is attached to private bonds in 29% (32%), whereas it is only observed approximately half as many times in public bonds (14% and 16%). Generally speaking, firms issuing private placement bonds appear to be more restricted in financing activities than firms issuing public placement bonds.

Turning to investment covenants, the sale of assets covenant (cov10) and activity restrictions (cov11) are statistically significant at the 1% level and with the expected negative sign. Measured by relative frequency, the sale of asset covenant is observed more (69%) in public than in private (58%) bonds, this difference significant at the 1% level, whereas the difference in the frequency of covenant 11 (activity restrictions) appears to be statistically insignificant. Other than expected, merger restrictions (cov15) are positively related to spread and significant at the 1% level. Interestingly, the use of merger restriction covenants is more often observed with the placement of public (67%) than that of private (58%) bonds. Although not statistically significant in the OLS regression, there is a significant difference in the use of cross default covenants. These are attached to 67% (58%) of the private (public) bonds in the sample. Generally speaking, firms issuing private placement bonds appear to be less restricted in investment activities than firms issuing public placement bonds.

Turning to other covenants, sale and leaseback restrictions (cov16) are more frequent in public (44%) than private (24%) bonds, the coefficient of those restrictions negative as expected and significant at the 5% level. Finally, privately placed bonds have a covenant attached that allows a majority of bondholders to change bond terms ex post in approximately one third (33%) of all cases, whereas publicly placed bonds have this covenant attached in only 14% of all bond issues, this difference significant at the 1% level.

Firms issuing private placement bonds appear to be more restricted in financing activities but less restricted in investment activities than firms issuing public placement bonds. These restrictions do in fact play an important role in explaining the excess spread of PPBs over PUBs. Restrictions related to financing activities appear to increase spread, those related to investment activities decrease spread. While firms that place bonds privately are more restricted in making distributions or placing additional debt, they are less restricted in the sale of assets, merger activities and sale and leaseback activities. Second, firms issuing private placement bonds are more subject to flexible debt renegotiation: the respective covenant (cov18) allows a supermajority of bondholders to consent to changes in the fundamental terms of the bond in 33% of all private bonds issued. Flexible debt renegotiation is, however, observed to a much lesser extent and only in 14% of all public bond issues.

4.3 Discussion

We have used covenant intensity, covenant factors and covenant dummy variables individually to explain the pricing differences between private and public placement bonds. Including the use of covenants in modelling bond spreads explains the pricing difference between the two placement channels. Moreover, the use of covenants also explains an important part of the variation in spreads of public bond placements.

Our findings are consistent with agency theory (Jensen & Meckling, 1976; Myers, 1977; Myers & Majluf, 1984) on the one side and incomplete contracting theory (Aghion & Bolton, 1992) on the other side. Consistent with the moral hazard hypothesis described earlier (see page 18) and the notion that firms that place bonds privately are more opaque (Krishnaswami et al., 1999), we find that covenants may lower spread by resolving agency problems.[21] Interestingly, while reducing the spread, given the difference in investment covenant frequencies, firms issuing private placement bonds appear to be less restricted in investment activities (that is the sale of assets and merger restrictions) than firms issuing public placement bonds. Leaning more on the debt renegotiation hypothesis and the results from our analysis using a binary choice model (Section 3) we find that firms place bonds privately in times of higher uncertainty. Private lenders request more restrictive covenants to manage events of adverse contingencies (Arena & Howe, 2009) when flexible ex post renegotiation and less damaging intervention in distress is focal (Detragiache, 1994; Cantillo and Wright, 2000). Increased monitoring and renegotiation efforts when contracting under higher uncertainty may lead investors to request compensation for these efforts. The observed ex ante restrictions related to financing are more frequently observed in private as opposed to public bond issues. The data suggests these restrictions related to distributions and additional debt are costly and increase spread.

Of course, there are likely other explanations explaining why financing covenants increase spread. For example, financing factor covenants may induce costs as they restrict managerial flexibility, as found by Kahan & Yermack (1998). The financing factor covenants may prevent the firm from making positive NPV investments, as these prevent it from taking on new debt. In addition, the financing factor covenants may induce costs because they may prevent firms to adjust their leverage to trade-off the costs and benefits of debt and obtain an optimal capital structure. As evidenced by Deangelo & Roll (2015), firms have different optimal leverage levels at different times, adjusting them regularly to maximize firm value. Devos et al. (2017) find that the presence of covenants significantly lowers the speed of capital structure adjustment. Using a covenant index, they find that - on average - firms with the highest index values take 26-31

[21] Underinvestment problems (Myers, 1977), asset substitution (Jensen & Meckling, 1976), or agency problems based on information asymmetries (Myers & Majluf, 1984).

months longer to adjust their capital structure than firms with no covenants. The effect of such other explanations, however, is left for future research.

5. Further Analysis and Robustness Tests

This section provides some further analysis of the main findings in Sections 3 and 4, as well as a number of robustness checks.

5.1 Covenants and economic uncertainty

Debt renegotiation is frequent in private credit agreements (Roberts and Sufi, 2009; Roberts, 2015). Our previous findings suggest that firms place bonds privately in times of higher uncertainty. In such times, lenders may request more covenants (Demerijan, 2017) to manage events of adverse contingencies, which in turn may accelerate the onset of debt renegotiation (Roberts, 2015) and increase the odds of renegotiating a debt contract (Nikolaev, 2017). Simultaneously, credit-supply frictions may influence the type and strictness of covenants in debt contracts (Christensen et al., 2019). As we find that the use of covenants and their impact on spread cannot be completely explained by either the issuer's economic fundamentals or the moral hazard hypothesis, we have proposed above that debt renegotiation and especially financing restrictions explain excess spread of private over public bonds. In line with Demerijan (2017), we suggest by our debt renegotiation hypothesis that the use of covenants is related to the state of economic uncertainty. Despite the fact that ex post debt renegotiation is typically dominated by investors, it frequently leads to covenant waivers, not covenant tightening, ex post (Garleanu & Zwiebel, 2009). We posit that investors may anticipate increased monitoring and renegotiation efforts when contracting under higher uncertainty and based on incomplete contracting theory.[22] As a consequence, investors may request compensation for their increased efforts ex ante, that is, they may require an increase in the yield spread.

As we have illustrated earlier, private placement bonds have more and different covenants attached than public placement bonds. We find that the private (public) bonds in our sample offer a supermajority of bondholders the ability to consent to changes in the fundamental terms of the bond in 33.4% (14.1%) of all issues, this difference being significant at the 1% level. Specifically, lenders appear to request more (less) restrictive financing covenants for firms issuing private (public) bonds. Financing covenants are observed in 31.9% (15.8%) of all private (public) bonds, this difference also significant at the 1% level.

We run additional OLS regressions to evaluate how bond spreads are affected by economic uncertainty. Our sample period comprises both the Global Financial Crisis (GFC; 4/2007-9/2009) and the subsequent European Debt Crisis (EDC; 3/2010-3/2012), allowing us to test for the effects of high economic uncertainty. We define the time of high economic uncertainty to be that following the onset of the GFC or the EDC. The time of low economic uncertainty is that for the periods twelve months prior to the onset of these two crises. Table 7 shows the results of our regressions using covenant intensity and the investment and financing factors. The regressions are specified as in Table 4, columns (8) and (9). For brevity, we only show the results with regards to covenant intensity and the use of the investment and financing factor in this additional analysis. We find strong support for the debt renegotiation hypothesis.

As illustrated earlier, financing covenants are only included after investment covenants and the upward sloping part of the U-shaped relationship between spread and covenant intensity is thus largely explained by financing covenants. These financing covenants explain our variable "covenant score squared" in specifications (1) through (4) and the financing factor used in specifications (5) through (7). The data suggests that covenant score squared is always significant at the 1% or five percent level in specifications (1) through (4). Importantly, discriminating

[22] see Grossman and Hart (1986), Hart and Moore (1988), Aghion and Bolton (1992) and Hart and Moore (1998) for a more complete review of the incomplete contracting theory and how mechanisms for revising the terms of trade ex post are structured.

between private and public bonds as in specifications (3) and (4), the effect of adding financing covenants in times of high uncertainty largely affects the pricing of private bonds, while it appears not to affect the pricing of public bonds. The interaction variable is statistically significant both for the linear and squared covenant score. The data suggests that firms issuing private (public) bonds in times of high uncertainty but with low covenant intensity experience higher (lower) effects from attaching covenants. However, the spread increases substantially when bonds with high covenant intensity are placed privately, whereas this is not priced in public bonds. For example, placing a bond privately (publicly) in high uncertainty but with average covenant intensity (7.5 covenants), the effect from the use of covenants is a spread reduction of approximately 112 (88) basis points.[23] Firms placing bonds privately experience a cost of debt that is lower by approximately -24 basis points, as compared to firms issuing public bonds. This favorable effect decreases monotonically in the number of covenants until approximately 12 covenants, as calculated from specifications (3) and (4) in Table 7. After this tipping point, the cost advantage turns into a cost disadvantage amounting to approximately 7, 17 and 28 basis points with 13, 14 and 15 covenants attached to a bond. The bond pricing difference between private and public bonds with an average (7.5) and a high (15) number of covenants attached thus amounts to approximately 52 basis points. This difference is also observed when using the financing factor in specification (6), for which the spread increasing effect is 52 basis points, significant at the 5% level.

This analysis provides additional evidence that, ceteris paribus, the use of covenants explains the excess spread of private over public bonds. Private bonds with only few covenants attached can be placed at a cost of debt that is lower than that of public bonds, on average. While the moral hazard hypothesis based on agency theory explains how the use of covenants reduces the cost of debt, we find that the debt renegotiation hypothesis, based on incomplete contracting

[23] For privately placed bonds and based on the coefficients in specification 3, the total spread given 7.5 covenants amounts to [7.5*-16.4] + [7.5*7.5*1.26] + [7.5*-25.2] + [7.5*7.5*2.29] = -112.3 basis points. For publicly placed bonds and based on the coefficients in specification 4, the total spread amounts to [7.5*-33.14] + [7.5*7.5*2.86] = -87.7 basis points.

theory, explains how the use of covenants may also increase the cost of debt. Investors may consciously accept increased monitoring and renegotiation efforts when contracting under high uncertainty and request compensation for these efforts. This appears to affect yield spreads accordingly.

5.2 Differences in the pricing of private versus public placement bonds

Section 4 shows that credit risk, liquidity, market conditions, and covenant use, together with control variables, jointly explain about 70% of the variation in spreads, and that the difference in spread between private and public bonds is importantly driven by the use of covenants. To analyze whether the effects of these variables are different for private and public placement bonds, we next include interaction terms for all variables with the placement dummy.

Table 8 shows the results. Columns one and three repeat the two final regressions from Table 4 with all variables included, using covenant score (squared) and the two covenant factors respectively. Columns two and four show the same regressions as in column one and three respectively, but with interaction terms for the placement dummy included. To save space, we only report coefficients for the interaction terms that are significantly different from zero.

Overall, the coefficients for the non-interaction terms do not change much when the interaction terms are included. Five interaction terms show significant coefficients for both specifications (with covenant score (squared) and with the covenant factors respectively), although in many cases only marginally so. First, whereas leverage has a small and insignificant effect on the spread for public placements, adding the interaction with placement indicates that there is a significant negative effect of leverage on the spread of private placement bonds. Second, the market volatility as measured by the VIX, appears to have a small and insignificant effect for public placement bonds, but a significant positive effect for private placement bonds - each percentage point increase in volatility being associated with about four basis points increase in the spread. Third, whereas returns on the own industry MSCI index for half a year preceding a bond issue does not affect public placement bonds, a one percent higher return on the own industry index leads to about a significant two basis points increase on the spread for private bonds. Fourth, whereas for public bonds, firms that are ten times bigger in assets would have a spread that is about 53 basis points lower than for otherwise comparable firms, for private bonds the spread would be a smaller 30-33 basis points lower (depending on specifications (2) versus (4)). Finally, whereas for public placements each percentage point increase in profitability lowers the spread by about 240 basis points, for private placement bonds, the lowering of the spread is only 55-85 basis points.

Three other variables - bond market liquidity, yield curve slope, and financing covenants - show up (marginally) significantly in only one of the two specifications when interacted with the placement dummy. Whereas the presence of finance covenants lead to an increase in spread of 28 basis points for public placements, an additional 43 basis points are added for private placements. This indicates that these covenants have stronger pricing effects.

Overall, we conclude that the most variables affect the spread in a similar way for public and private placement bonds. Private placement bond spreads are slightly more sensitive to bond market liquidity and the slope of the yield curve, and are more strongly affected by financing covenants.

5.3 The pricing of private placement bonds during financial crises

As our sample period comprises both the Global Financial Crisis (GFC; 4/2007-9/2009) and the subsequent European Debt Crisis (EDC; 3/2010-3/2012), in this section we check whether the pricing of private versus public placement bonds is different during periods of crisis. Friewald et al. (2012) and Dick-Nielsen et al. (2012) for example, find that the GFC led to a deterioration of market liquidity and our results so far indicate that spread also depends on liquidity. Additionally, Longstaff et al. (2011) show that in periods of crisis, credit spreads seem to depend more on a common set of global factors such as the volatility risk premium embedded in the VIX index. Thus, the pricing of public and private bonds may indeed be different during crises.

To analyze the effect of different crisis periods on the spreads, we use dummy variables to identify different subperiods. The dummies indicate the periods i) before the onset of the GFC, ii) during the GFC, iii) after the GFC, iv) during the EDC, and v) after the EDC. For these different subperiods we run regression (9) as in Table 3, with the period dummy and the period dummy interacted with the private placement dummy added. The results are reported in Table 9.

First, looking at the credit, liquidity, market conditions, agency costs, and control variables, we see that the estimates are very similar across the different specifications, and also to the estimates for the benchmark specification (9) in Table 4. Next, looking at the periods before, during, and after the GFC (specifications (1), (2), and (3) in Table 9, we first see that average excess spreads are a significant 82 basis points lower before the GFC as witnessed by the large and highly significant pre-GFC dummy in specification (1). During the crisis, the crisis-dummy in specification (2) implies that spreads were on average 47 basis points higher compared to the periods before and after the GFC. After the GFC, as can be seen from specification (3), spreads are not different from the period before the end of the GFC, controlling for all other factors in our regression model.

The fact that in all three of these specifications the interaction term between the three periods and the placement dummy does not show any significant effect, implies that the lower spreads before the GFC and the higher spreads during the GFC apply to both public and private bonds. The effect of the GFC does not affect public and private bond spreads in different ways.

Specifications (4) and (5) show that this is different for the periods during and after the EDC. These period-dummies show significant effects only when interacted with the placement dummy. Thus, the EDC appears to affect especially private bond spreads, not public bond spreads. During the EDC, private bond spreads were about 53 basis points higher than public bond spreads, controlling for all other factors. Contrary, after the EDC, private bond spreads were about 60 basis points lower than public bond spreads.

Thus, although our findings for the entire sample suggest that credit risk, liquidity, market conditions, and agency costs together with a set of control variables can explain the difference in spreads between private and public debt, for the periods during and after the EDC we still find differences in pricing to the two types of bonds.

5.4 Out-of-sample test

Next, we conduct an out-of-sample test on 1,865 Euro denominated publicly placed corporate bonds to evaluate the ability of the model developed above to fit market prices. As in Eom et al. (2004) we consider the error in spread to be the most informative measure of model performance. [24]

First, we compare the predicted bond spreads from our model to the observed bond spreads. Estimating spreads using the empirical model developed and shown in specification 7 of Table 4, the model predicts an average spread of 210 basis points (with a standard deviation of 174 basis points). The observed spread is 221 basis points (with a standard deviation of 237 basis points). The model thus slightly under-predicts spreads by 11 basis points or -4.7% (observed minus predicted spread scaled by observed spread). This result compares to Eom, Helwege, & Huang (2004), who empirically test five well-known bond pricing models (see Table 3, column 5 in their paper). In particular, they analyse the models of Merton (1974), Geske (1977), Longstaff and Schwartz (1995), Leland an Toft (1996), and Collin-Dufresne and Goldstein (2001). Their carefully calibrated models predict bond spreads with errors between -53% and 270%, with the lowest prediction error rendering an underprediction of -6.6% and the second best prediction error rendering an overprediction of 43%. These results compare to the underprediction of 4.7% using our model. The spread prediction error of our model including covenant use appears to be markedly lower than that from the models tested in Eom et al. (2004). We also find that the out-of-sample R^2 of the model is a relatively high 29% and the correlation between the out-of-sample excess spreads and the model-predicted spreads is 0.56.

[24] We are now using the maturity matched German government bond to calculate spreads.

Next, we evaluate if and how the reliability of the model is affected by the inclusion of the covenant factors. We re-run the same prediction, this time excluding covenant intensity. Once covenant intensity is excluded from the prediction, the model predicts a spread of 268 basis points (with a standard deviation of 150 basis points). The spread prediction error thus jumps to a level of -47 basis points or -21%.

Overall, while the aforementioned five structural bond pricing models tested in Eom et al. (2004) appear to have difficulty in accurately predicting credit spreads, our results suggests that a model including covenant factors predicts spreads with more accuracy.

5.5 Robustness tests

As a final part of our analysis, we address a number of econometric issues and robustness tests. First, as Bradley & Roberts (2015) find that covenant structure and yields on corporate loans are determined simultaneously, this may also be the case for our sample of bonds. Therefore, following Demiroglu & James (2010), we use Instrumental Variables for covenant score (squared), using an investment grade dummy, leverage, EBITDA divided by revenues, age, bond maturity, and the ratio of issue amount to total assets as instruments. The two-stage least squares estimates for the Instrumental Variables regressions are reported in Table 10, specification (2) and (3).[25] Specification (2) uses covenant score (squared), whereas specification (3) uses the two covenant factors. The results show that we cannot reject the hypothesis that covenant score (squared) is exogenous and the estimated coefficients are very close to those reported in Table 4 with an adjusted R^2 that is only a bit lower than the one in the baseline model (8) in Table 4 (62% versus 71%) and likewise in the baseline model (9) in Table 3 (66% versus 73%). This suggests that our earlier results do not arise from a significant endogeneity bias.

Second, next to the covenant structure, bond characteristics like maturity, issue amount, and (top tier) bank involvement may be subject to simultaneity bias as well. As noted by Prilmeier

[25] To avoid multicollinearity problems, we exclude variables that are used as instruments, such as leverage, as independent variables in the regression.

(2017) and Demiroglu & James (2010), it is difficult to identify exogenous variables to instrument for these contract terms. We therefore follow Demerjian (2017) and Reisel (2014), and check the robustness of our findings by excluding bond characteristics maturity, (log) amount, and top tier bank involvement, that are potentially subject to a simultaneity bias. The results, reported in Table 10, specification (4), show that excluding these variables does not change our main findings.

Third, in our main analysis, for bond issues without covenant information, we set the covenant value to zero. This contrasts to, e.g., Hollander & Verriest (2016), who exclude contracts with no covenant information. We rerun regression (8) from Table 4, excluding bond issues without covenant information, thereby lowering our sample size from 685 to 600 issues. Specification (5) in Table 10 shows the results for this smaller sample. Although unlike in Table 4, the coefficients for issue amount and profitability now become insignificant, we still find that the difference in spread between private and public placement bonds is small and insignificant, and that the effect of the covenant factors does not change from the results in Table 4.

Fourth, as our volatility measure, VIX, is from the U.S. stock market, whereas the bonds in our sample are all issues by European companies, we rerun regression (8) from Table 4 using two European volatility indices: VSTOXX, an index jointly developed by the German Stock Exchange and Goldman Sachs that measures Eurozone stock market volatility based on Euro STOXX 50 index options and VDAX, which is the German equivalent of the VIX index, also used by e.g. Acharya et al. (2014). Specifications (6) and (7) in Table 10 show the results using these two indices, which are very similar to Table 4. This suggests that a global component in stock market volatility is the most relevant one for the pricing of bonds.

Fifth, as previous studies distinguish between 144A registered bonds (Fenn, 2000, Chaplinsky & Ramchand, 2010, Arena, 2011) and non-144A (Kwan & Carleton, 2010, Arena, 2011), we add a dummy for whether a bond is 144A registered or not. 144A registration allows a private bond to become registered (public) at a later stage. Specification (8) in Table 10 shows, the 144A-dummy is insignificant, indicating that 144A registered bonds are not priced differently than non-144A registered bonds.

Sixth, one may argue that firms issuing PPBs that are stock-listed face less agency problems given higher disclosure and reporting requirements. To test this, we run specification (9) in Table 10 using only stock-listed bond issuers. The restricted sample amounts to 614 issues. The results remain mainly unchanged and the coefficients on the linear (squared) covenant factor of the regression are -25.82 (55.67), both significant at the 1% level, the placement variable insignificant (t=0.17).

Seventh, Kwan and Carleton (2010) find that pricing differences disappear for issuers that use both private and public placements, which they call switchers. We therefore analyze bond issues of switchers only. 382 bonds are issued by switchers. As is shown in specification (10) in Table 10, the coefficients on the investment and financing factors remain almost unchanged, the placement variable again being insignificant (t=0.08). Controlling for switchers appears to leave the results unchanged.

Eighth, we include year fixed effects in the regression. In specification (11) in Table 10, the coefficients for the covenant factors are very similar to the ones in Table 3 and the difference in spread between private and public placement bonds is an insignificant two basis points - implying that our main results still hold. The inclusion of year fixed effects does impact some of the other variables though. In particular, the effects of both stock and bond market liquidity become insignificant.

Finally, better accounting quality may ameliorate information asymmetry between a firm and investors (Ball, 2001), reduce uncertainty about credit risk (Akins, 2018) and excert influence on a bond issuer's choice of private versus public debt (Bharath et al., 2008). Accounting quality may thus affect both the choice for or against issuing a bond privately and its pricing. We control for the effects of accounting quality, which in general involves the use of stricter standards for recognizing bad news as losses than for recognizing good news as gains (Lafond & Roychowdhury, 2008). First, we are interested whether accounting quality affects the choice of a firm for private versus public bonds placements in our sample, potentially causing concerns related to endogeneity. Second, we test whether the observed excess spread is not simply a result of differences in accounting quality between firms issuing public versus private bonds. Based on the findings of Lin et al. (2012) and Barth et al. (2006), we assume accounting quality is higher for firms applying US Generally Accepted Accounting Principles (US GAAP) than for firms applying International Financial Reporting Standards (IFRS) or other International Accounting Standards (IAS), such as various European GAAP standards.[26] We proxy for accounting quality using a dummy variable taking the value of one if an issuer applies US GAAP, IFRS or IAS, zero otherwise.[27] We use the binary choice model (Table 3) and the regression model (Table 4) presented earlier and add these proxies for accounting quality. The expectation is that better accounting quality as proxied by the use of US GAAP decreases the odds of placing a bond privately, while it should increase for firms using inferior accounting quality as proxied by the use of IFRS or IAS. The results are presented in Table 11. Using our choice model, the dummy variables in specifications (1) through (3) are not significant. Looking at the odds ratios, the likelihood that a bond is placed privately increases (ratio is > 1) for firms using IFRS or IAS and decreases (ratio is < 1) for those using US GAAP. So while the odds ratio is in line with our predictions, we find no statistically significant influence of accounting quality on the choice for private versus public debt. Next, we verify whether accounting quality affects spreads and the pricing difference between private over public bonds. We include the same dummy variables in specifications (4) through (6). Accounting quality appears to affect spreads in an economically important and meaningful way. Better

[26] Lin et al. (2012) find that the application of US GAAP generally results in higher accounting quality than the application of IFRS. According to them, accounting numbers under IFRS generally exhibit more earnings management, less timely loss recognition, and less value relevance compared to those under US GAAP. Barth et al. (2006) find that IAS firms, compared to US firms applying US GAAP, exhibit lower accounting quality in terms of earnings smoothing, the correlation between accruals and cash-flows, timely loss recognition, and the association between accounting amounts and share price.

[27] Direct measures of accounting quality, for example the sensitivity of earnings per share of bad relative to the sensitivity of good news, the explanatory power (R^2) of bad relative to that of good news, the time-series skewness of earnings deflated by that of cash-flows or accumulated non-operating accruals deflated by total assets, as used for example in Zhang (2008), could provide better proxies for accounting quality. Bharath et al. (2008) proxies accounting quality using deviations from expected operating accruals. More recently Kraft (2015) or Akins (2018) use rating agency adjustments to firms' reported GAAP financial statement or the explanatory power of changes in reported earnings on rating downgrades, respectively, to proxy for financial statement or reporting quality. The application of such measures, however, is beyond the scope of this study.

accounting quality (US GAAP) reduces spread by a significant 29 basis points, while worse accounting quality (IFRS) increases spread by approximately 40 basis points, the results significant at the 1% and 5% level. The dummy variable for the use of IAS, that is national GAAPs, is statistically not significant. Importantly, our findings related to covenant intensity remain almost unaffected by the inclusion of the accounting quality proxies. The coefficients of covenant intensity and its squared value, compared to Table 4, specification (8), remain almost unchanged. Also, the placement variable remains insignificant. However, running an untabulated regression including the accounting quality variables but excluding covenant intensity (and its squared value), the excess spread of private over public bonds remains at a significant 27 basis points. This compares to specification (3) in Table 4 and 42 basis points of excess spread prior to controlling for the use of covenants. We therefore conclude accounting quality further explains the excess spread of private over public bonds. However, it is only when we include covenant intensity that the excess spread becomes insignificant. Covenant intensity and its squared value remain highly statistically significant and the observed non-linear relationship between covenant intensity and spread remains unaffected.

Overall, these results imply that our main findings are robust in various dimensions.

6. Conclusions

This paper analyzes the effect of covenant use on bond pricing using primary market bond data of 690 private placement bonds versus 527 public placement bonds, issued by 310 different European companies in the years 2002 to 2015. We find that on average private placement bonds have an excess spread over public placement bonds (both spreads calculated from the maturity matched government bond) of 116 basis points.

We find that firms place bonds privately in times of higher uncertainty about future economic events. In such times, private debt provides an option for flexible debt restructuring ex post. Avoiding premature and costly liquidation observed with public debt, investors appear to require and private debt issuers appear to accept more covenants and an ex ante increase in the cost of debt to buy an option for flexible debt restructuring ex post.

In line with this conjecture, only about 50% in the variation in spreads on both private and public placement bond spreads can be explained by credit risk variables. Including covenant use increases the R^2 more than including liquidity or market condition variables, implying that the use of covenants can explain as much of the variation in spreads as liquidity and market conditions together. Adding liquidity, market conditions, and control variables, more than 70% of the variation in spreads can be explained. Importantly, the data suggests the difference in spreads between private and public placement bonds can only be fully explained once covenant use is considered.

We find that, broadly speaking, there are two groups of covenants - investment and financing covenants - which are mainly added to bonds in that order. Investment covenants restrict a firm from making investment decisions and selling its assets. Their presence reduces the spread on bonds as they alleviate moral hazard problems. Financing covenants are typically added on top of investment covenants, the relationship between the spread and covenant intensity (i.e., the number of covenants used) is U-shaped. The different use of covenants in private versus public placement bonds explains an important part of the difference in spread witnessed by these two types of bonds.

With only a few exceptions, most of our variables have a similar effect on public and private placement bond spreads. Most notably, we find that the pricing of private placement bonds are more sensitive to stock market volatility, recent stock market returns for the own industry, and for the use of investment covenants. Also, whereas otherwise comparable bigger firms pay lower spreads, this effect is smaller for private than for public placement bonds.

During the global financial crisis spreads were higher on both public and private placement bonds, but there was no notable difference in the pricing of the two types. During the European debt crisis on the other hand, spreads on private placement bonds were more strongly affected than spreads on public placement bonds.

Most importantly, we find that the observed difference in credit risk amounts to a difference in spreads of 465 basis points, whereas the observed difference in covenant use amounts to about 400 basis points: the use of covenants is therefore equally relevant in explaining spreads as is credit risk. The fact that the price difference between private and public placement bonds are only explained once covenant use is controlled for. Also, the finding that the use of covenants together with liquidity, market conditions, and added control variables, explain a large part of the variation in spreads, appear to be robust in many dimensions.

Using an out-of-sample test and predicting spreads of Euro denominated primary market bond issues, the predictions errors from a model including (excluding) the use of covenants are substantially lower (higher), suggesting covenant use is an important factor in explaining bond pricing.

There are likely other explanations explaining why financing covenants increase spread. Candidates for future research include the analysis of financing factor covenants and their costs related to the restriction of managerial flexibility (see Kahan & Yermack, 1998) and their costs related to them preventing firms to adjust to optimal leverage levels (see Deangelo & Roll, 2015). Devos et al. (2017), for example, find that the presence of covenants significantly lowers the speed of capital structure adjustment. Using a covenant index, they find that, on average, firms with the highest index values take 26-31 months longer to adjust their capital structure than firms with no covenants. Additionally, it would be interesting to learn more about the information disclosure hypothesis (see footnote 13). The effect of such other explanations, however, is left for future research.

We have controlled for the potential endogeneity of the use of covenants and yield spread using a 2SLS estimation procedure. Of course, there may be other elements of the contracting process (e.g. the choice of a top tier arranger or bond maturity) that may be endogenous or simultaneously determined. The effect of such additional complications is, however, left for future research.

7. Tables

Table 1: Descriptive Statistics on Private over Public Placement Bonds

This table presents descriptive statistics for private and public placement bonds issued in Europe from 2002 through 2015 for those bond characteristics (Panel A), firm characteristics (Panel B) and market conditions (Panel C) used as variables in this study and as defined in Appendix A. Δ is the difference between PPB over PUB . Two tailed statistical significance is denoted ***, ** , and * at the 1 %, 5 % and 10 % level respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Private			Public			
Panel A: Bond characteristics	**mean**	**median**	**n**	**mean**	**median**	**n**	**Δ, t-value**
spread	402.05 (242.01)	396.59	676	285.75 (299.28)	199.88	514	116.3***
maturity	8.95 (5.86)	8.01	690	9.16 (7.40)	6.98	527	-0.21
amount	508.03 (441.80)	389.00	663	469.80 (484.76)	366.00	517	38.23
top_tier	0.49 (0.50)	0.00	690	0.39 (0.49)	0.00	527	0.10 ***
covscore	7.42 (5.26)	9.00	690	6.63 (4.23)	8.00	527	0.79 ***
options	0.80 (0.40)	1.00	690	0.76 (0.42)	1.00	527	0.04*
Panel B: Firm characteristics	**mean**	**median**	**n**	**mean**	**median**	**n**	**Δ, t-value**
age	56.00 (53.64)	35.00	521	46.83 (43.76)	34.00	467	9.17***
assets	28320 (55951)	8057	523	43442 (57589)	17710	427	15121.67***
revenues	14020 (23077)	3956	521	21413 (26095)	10935	423	-7392.25***
leverage	0.34 (0.23)	0.27	510	0.29 (0.21)	0.23	415	0.05***
listed	0.55 (0.50)	1.00	690	0.66 (0.47)	1.00	527	-0.12***
profitability	0.15 (0.18)	0.15	522	0.15 (0.21)	0.17	421	0.01
rating score	9.48 (2.61)	9.00	503	8.57 (3.48)	8.00	403	0.91***
Panel C: Market Conditions	**mean**	**median**	**n**	**mean**	**median**	**n**	**Δ, t-value**
gdp_360	-0.14 (0.40)	-0.20	690	-0.09 (0.46)	-0.10	527	-0.05*
mscii_180	6.27 (14.31)	6.66	690	4.29 (16.93)	6.43	527	1.98**
msciitot_180	4.48 (12.81)	6.94	690	4.15 (16.00)	7.87	527	0.33
slope	1.78 (0.69)	1.74	690	1.62 (0.90)	1.83	527	0.15***

Table 1: Descriptive Statistics on Private over Public Placement Bonds (continued)

benchmark	2.43	2.18	690	2.95	3.03	527	-0.53***
	(1.20)			(1.41)			
refcorp liquidity	0.53	0.49	690	0.52	0.47	527	0.01
	(0.24)			(0.31)			
stock market liq.	-0.02	0.00	690	-0.02	-0.01	527	0.00
	(0.07)			(0.07)			
VIX	17.89	15.73	685	19.38	16.86	525	-1.49***
	(6.72)			(8.48)			
rolscore	8.29	8.53	690	8.32	8.48	527	-0.03
	(0.70)			(0.63)			

Table 2: Riskadjusted Excess Spreads of Private Placement Bonds (PPB) by Rating score and Maturity

This table presents risk adjusted spreads (residuals) from the postestimation of an OLS regression of spread on credit risk. Bivariate comparisons of observed and estimated riskadjusted spreads of private bonds and pubilc bonds from 2002 through 2015 sorted by different criteria is given in Panels A, B and C. Regressing spread on rating score renders an adjusted R^2 of 40.35% with t = 43.4, p<0.001 for rating score and a constant of -160.85 (t=-14.77). The coefficient is 49.06 and indicates the increase in spread per one unit change in rating score (with min. = 1 and max. = 18). The mean residuals values of PPB (r_ppb) and PUB (r_pub) indicate excess spread after correcting for credit risk as measured by credit score. The difference between r_ppb over r_pub is indicated in the row "Δ mean residuals" together with Wilcoxon rank sum test results. T-values from a student t-test are in the next row. Two tailed statistical significance is denoted ***, ** , and * / at the 1 %, 5 % and 10 % level respectively.

	All	Private Placement Bonds (PPB)			Public Placement Bonds (PUB)			PPB vs. PUB	
	n Bonds	n Bonds	Observed Spread (s_ppb)	Mean Residuals (r_ppb)	n Bonds	Observed Spread (s_pub)	Mean Residuals (r_pub)	Δ mean Residuals (r_ppb - r_pub)	t-value
Panel A: By Rating score									
All	817	488	377.59	17,38	329	284.37	-25.79	43.17***	3.85
AA-	17	2	50.76	-20.74	15	131.75	60.24	-80.99	-1.20
A+	36	18	128.78	4.51	18	77.78	-46.49	51.00***	5.13
A	43	30	189.39	12.36	13	116.04	-61.00	73.35**	2.28
A-	138	69	200.63	-29.44	69	168.29	-61.52	32.08***	1.56
BBB+	96	46	277.76	-4.81	50	208.58	-73.99	69.19**	2.37
BBB	159	118	345.54	10.20	41	274.63	-60.71	70.92**	2.37
BBB-	60	38	469.31	81.20	22	293.68	-94.43	175.63***	4.13
BB+	72	55	543.93	103.06	17	578.19	137.32	-34.26	-0.61
BB	63	51	504.99	11.35	12	470.77	-22.87	34.22	0.62
BB-	35	20	595.38	48.98	15	580.70	34.30	14.68	0.30
B+	31	20	550.23	-48.95	11	643.97	44.79	-93.74*	-1.85
B	25	11	553.42	-88.52	14	695.39	43.45	-131.98*	-1.81
B-	3	1	453.50	-251.21	2	496.25	-208.46	-42.75	n.a.
CCC+	10	4	856.95	108.47	6	604.30	-153.18	261.65**	2.23
CCC or lower	4	2	826.00	15.76	2	583.00	-227.24	243.00***	8.38
Panel B: By Maturity									
Short mat.	419	226	459.69	37.09	193	369.84	-24.89	61.98***	3.07
Medium mat.	548	373	408.04	14.52	175	316.08	-18.68	33.20**	2.12
Long mat.	104	48	202.56	-35.59	56	170.02	-47.83	12.25	0.52
Panel C: By Industry									
Consumer discr.	94	72	342.13	-3.46	22	447.37	49.67	-53.14	-1.63
Consumer stpls.	73	57	254.23	-46.86	16	270.87	-57.87	11.01	0.28
Energy	123	53	502.25	70.35	70	369.35	47.58	22.77	0.66
Healthcare	122	59	269.37	-27.51	63	157.95	-53.41	25.90*	1.28
Industrials	110	63	413.10	65.20	47	277.49	-65.70	130.9***	3.84
IT	18	13	391.80	-81.55	5	294.50	-83.05	1.50	0.03
Materials	113	82	445.80	28.73	31	360.33	-9.05	37.79	1.09
Telecoms	103	48	537.82	58.47	55	268.71	-64.71	123.18***	4.25
Utilities	61	41	222.89	26.55	20	155.64	-63.61	90.16***	2.58

Table 3: Binary Choice Model

Estimates from multinomial logistic regressions predicting the source of 684 primary market bond issues during 2002–2015. The binary choice consists of privately placed bonds (1) versus publicly placed bonds (0). In column (1), we use all bond issues. In columns (2), we restrict the sample to bond issues of firms that use both the private and the public market. We call these issuers switchers. In column (3), we restrict the sample to those bond issues of firms that place either in the public or in the private market. We call these issuers nonswitchers. Odds ratios indicate the likelihood of a firm placing bonds privately versus publicly. The percentage change in odds for a standard deviation increase in the used variables is indicated in brackets. The pseudo-R^2 is from McFadden (1974). Two tailed statistical significance is denoted ***, ** and * indicating the 1 %, 5 % and 10 % significance level respectively.

Odds Ratio (% change in odds for a SD increase in X)	**(1) All issues**	**(2) Switchers**	**(3) Nonswitchers**
rating_score	0.940	0.908	1.157
	(-17.2)	(-26.9)	(48.5)
leverage	0.882	0.361	2.444
	(-2.1)	(-15.6)	(15.8)
issue amount (log)	2.337***	1.931***	4.192***
	(103.2)	(60.2)	(290.7)
stock market liquidity	0.0632**	0.0452	0.265
	(-18.3)	(-21.1)	(-8.6)
refcorp liquidity	0.831	0.371	3.991
	(-5.2)	(-26.3)	(42.8)
VIX	0.973	0.885***	1.106***
	(-19.3)	(-63.3)	(107.5)
top tier arranger	2.099***	3.066***	1.475
	(109.9)[1]	(206.6)[1]	(47.5)[1]
age (log)	1.855***	1.438	2.197**
	(35.2)	(14.9)	(55.4)
benchmark interest rate	1.093	1.660***	0.776
	(11.4)	(81.4)	(-27.5)
yield curve slope	1.325**	1.628**	1.307
	(21.1)	(37.7)	(20.7)
GDP growth (360d)	0.688	1.116	0.486*
	(-14.5)	(4.6)	(-26.7)
MSCI industry return (180d)	0.998	0.960***	1.047***
	(-2.23)	(-48.0)	(90.7)
rule of law	0.561***	0.544**	0.727
	(-32.2)	(-31.5)	(-20.8)
assets (log)	0.691***	0.734**	0.550***
	(-46.6)	(-40.2)	(-64.5)
profitability	0.307	0.274	0.173
	(-17)	(-19.8)	(-21.9)
maturity	0.999	0.970	1.029
	(-0.8)	(-20.1)	(24.7)
stock listing	0.673	1.887	0.306**
	(-11.3)	(18.7)	(-33.1)
rating_score*time	1.018***	1.026***	1.008
	(105.5)	(174.9)	(42.7)
constant	4.838	9.826	0.0168
	(11.58)	(38.05)	(0.0514)
Observations	684	382	302
pseudo-R^2	15.63	19.36	27.62

[1] «top-tier» is a binary variable indicating whether a top-tier bank was involved in a bond placement. The percent change in odds in brackets does therefore not indicate the change for a one standard deviation but for a top-tier bank being involved (1) or not (0).

Table 4: Empirical Model of Excess Spread

This table reports the estimates from the cross-sectional regressions of spread on a set of proxies for credit risk (1), liquidity (2), market conditions (3) and firm controls (7) as well as the placement dummy variable as defined in equation (1). The placement variable indicates the excess spread of PPBs over PUBs. Heteroskedasticity-robust standard errors are in parenthesis. Covenant score with (without) the quadratic term is used in specification 4 (5). In specification (9), the investment covenant and the financing covenant factor are used. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Robust standard errors in parentheses. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Credit Risk	Credit Risk and liquidity variables	Credit Risk and Market Conditions	Credit Risk and Agency Costs	Credit Risk and Agency Costs	Credit Risk, Liquidity, Market Conditions, and Agency Costs	Credit Risk, Liquidity, Market Conditions, and Agency Costs, with firm control variables	Credit Risk, Liquidity, Market Conditions, and Agency Costs, with firm control variables and industry dummies	Credit Risk, Liquidity, Market Conditions, and Agency Costs, with firm control variables and industry dummies, covenant factors
constant	-153.7***	-171.3***	-98.73	19.88	142.2***	341.9***	682.8***	671.0***	663.9***
	(16.43)	(55.04)	(78.3)	(31.83)	(33.58)	(90.64)	(99.63)	(106.7)	(99.78)
placement	45.65***	46.64***	42.32***	43.27***	12.68	12.55	9.603	4.615	2.931
	(11.88)	(11.45)	(11.37)	(11.95)	(11.44)	(11.07)	(10.73)	(11.63)	(11.19)
rating score	52.04***	53.38***	53.78***	47.09***	39.62***	40.22***	33.01***	25.86***	20.96***
	(2.477)	(2.569)	(2.447)	(2.683)	(2.66)	(2.663)	(3.493)	(4.05)	(3.855)
leverage	-27.19	-16.71	-20.09	-115.6**	-152.3***	-113.3**	-109.0**	-64.07	-62.57
	(31.1)	(33.14)	(31)	(48.2)	(48.44)	(46.54)	(45.17)	(46.99)	(46.16)
issue amount (log)		-16.48**				-12.90*	12.23	21.91**	25.57***
		(7.579)				(7.529)	(8.526)	(8.545)	(8.072)
stock market liquidity		-120.3*				-206.8***	-191.1***	-192.9***	-168.5**
		(72.58)				(77.69)	(70.84)	(68.43)	(67.97)
refcorp liquidity		-175.8***				-112.9***	-114.6***	-111.2***	-108.3***
		(17.27)				(26.14)	(25.2)	(23.9)	(24.43)
VIX			4.024***			1.479	1.548	2.491**	3.009***
			(0.911)			(1.037)	(1.005)	(1.012)	(1.002)
benchmark interest rate			-17.15***			-9.359**	-22.39***	-22.77***	-25.57***
			(4.64)			(4.346)	(6.718)	(6.502)	(6.525)
yield curve slope			9.162			-5.274	-1.767	-3.857	1.058
			(7.639)			(7.848)	(7.809)	(8.074)	(7.957)
GDP growth (360d)			-31.42**			-27.17**	-26.55**	-27.73**	-25.48**
			(13.3)			(13.69)	(12.9)	(11.88)	(11.49)
MSCI industry return (180d)			-0.911*			-0.769	-0.771	-0.0998	0.168
			(0.469)			(0.511)	(0.49)	(0.491)	(0.482)
rule of law			-14.40*			-23.00***	-27.75***	-24.72***	-23.60***
			(8.436)			(8.381)	(7.793)	(8.371)	(7.617)
covenant score				**1.826**	**-42.14*** **	**-38.84*** **	**-31.08*** **	**-32.52*** **	**-21.14*** **
(9: investment covenants)				(1.438)	(4.764)	(4.469)	(4.575)	(4.473)	(5.755)
covenant score squared					**3.494*** **	**3.342*** **	**2.682*** **	**2.749*** **	**62.81*** **
(9: financing covenants)					(0.365)	(0.344)	(0.363)	(0.362)	(7.636)
top tier arranger				5.674	9.942	9.353	9.519	1.226	-4.318
				(11.73)	(10.82)	(10.51)	(9.97)	(9.772)	(9.432)
age (log)				-81.76***	-61.92***	-76.68***	-75.20***	-39.34***	-36.76***
				(12.58)	(12.53)	(12.32)	(11.59)	(13.07)	(12.69)
assets (log)							-30.07***	-41.64***	-44.08***
							(5.679)	(6.654)	(6.237)
profitability							-101.4***	-118.2***	-132.0***
							(33.03)	(32.28)	(31.89)
bond maturity							1.081*	1.262**	1.861***
							(0.575)	(0.553)	(0.575)
stock listing							-62.27***	-67.34***	-67.33***
							(22.91)	(22.18)	(20.84)
credit rating * time							-0.374	-0.235	-0.172
							(0.261)	(0.271)	(0.266)
Observations	797	778	793	692	692	684	684	684	684
Adjusted R-squared	0.507	0.564	0.56	0.526	0.583	0.661	0.688	0.714	0.731
F		182.8	137.1	128.9	136.5	76.51	66.6	59.04	63.03
Benchmark industry								Industrials	Industrials

Table 5: Conditional Frequency of Investment and Financing Covenants

This table oders investment (covenants 3, 11, 6, 9, 14, 8, 10 and 15) and financing covenanst (2, 7, 1, 17) with a minimum factor loading of 0.5 given the factor analysis. It presents average conditional frequencies per covenant and allows to analyze, in how many bonds, on average, factors 1 and factor 2 are represented, conditional on a covenant being attached to a bond. The rectangular box says that in 96 % of all cases (32 values) when a bond has financing covenants attached, is also has investment covenants attached. Bonds that have investment covenants attached, however, only have also financing covenants attached in 47%. of all cases.

	Factor 1: Investment Covenants								Factor 2: Financing Covenants			
	cov3	cov11	cov6	cov9	cov14	cov8	cov10	cov15	cov2	cov7	cov1	cov17
Loadings Factor 1	**0.67**	**0.95**	**0.88**	**0.95**	**0.95**	**0.68**	**0.77**	**0.77**	0.47	.	.	.
Loadings Factor 2	.	.	.	.	.	0.32	0.40	0.38	**0.58**	**0.92**	**0.89**	**0.88**
Frequency	0.82	0.69	0.66	0.66	0.66	0.60	0.59	0.58	0.40	0.29	0.29	0.27
cov3	**Factor 1**	0.83	0.79	0.80	0.80	0.73	0.71	0.70	0.49	0.35	0.35	0.33
cov11	1.00	.	0.95	0.95	0.95	0.85	0.84	0.83	0.58	0.42	0.41	0.40
cov6	1.00	1.00	.	0.95	0.95	0.86	0.83	0.82	0.59	0.43	0.42	0.41
cov9	1.00	1.00	0.95	.	1.00	0.85	0.84	0.83	0.58	0.41	0.40	0.39
cov14	1.00	1.00	0.95	1.00	.	0.85	0.84	0.83	0.58	0.41	0.40	0.39
cov8	1.00	0.97	0.94	0.93	0.93	.	0.81	0.80	0.58	0.46	0.46	0.44
cov10	1.00	0.99	0.93	0.94	0.94	0.83	.	0.98	0.68	0.49	0.48	0.46
cov15	1.00	0.99	0.93	0.94	0.94	0.83	0.99	.	0.68	0.48	0.48	0.46
cov2	1.00	0.99	0.96	0.95	0.94	0.86	0.99	0.97	**Factor 2**	0.62	0.62	0.61
cov7	1.00	0.99	0.96	0.92	0.92	0.95	0.98	0.96	0.85	.	0.92	0.89
cov1	1.00	0.99	0.96	0.93	0.93	0.97	0.99	0.96	0.88	0.94	.	0.87
cov17	1.00	1.00	0.98	0.93	0.94	0.96	0.99	0.97	0.90	0.96	0.91	.
Minimum	1.00	0.83	0.72	0.58	0.58	0.68	0.71	0.70	0.49	0.34	0.32	0.33
Avg. cond. frequency	1.00	0.97	0.93	0.91	0.91	0.85	0.91	0.88	0.70	0.58	0.57	0.50
Maximum	1.00	0.99	0.95	0.94	0.94	0.85	0.96	0.84	0.67	0.49	0.48	0.46

Table 6: Empirical Model of Excess Spread using Covenant Dummy Variables

This table reports the estimates from the cross-sectional regressions of spread on a set of covenant dummy variables, the covenants as described in Appendix C, and additional variables as in Table 4. The placement variable indicates the excess spread of PPBs over PUBs. Heteroskedasticity-robust standard errors are in parenthesis. Covenant score with (without) the quadratic term is used in specification (1), the baseline regression as in Table 4, specification 8. In specification (2), covenant dummies are used. Columns (3) and (4) indicate the frequency of covenants used for private and public bond placements respectively, together with the test for the difference between the two placement channels as measured by the ranksum test (z). The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Robust standard errors in parentheses. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

VARIABLES	(1) Baseline with covscore	(2) Covenants used as dummies	(3) Frequency PPB in %	(4) Frequency PUB in % (z)
Financing covenants (+)				
cov1 distributions		64.64**	29.02	13.76***
		(26.61)		
cov2 financial statements		7.966	43.78	35.23**
		(114.29)		
cov7 limit of indebtedness		79.71***	31.87	15.77***
		(32.62)		
cov17 subsidiary debt		20.89	31.87	12.08***
		(34.92)		
Investment covenants (-)				
cov3 default info		-8.058	86.79	88.59
		(24.40)		
cov6 negative pledge		49.54*	72.02	71.81
		(26.21)		
cov8 cross default		4.013	68.65	58.39***
		(13.47)		
cov10 sale of assets		-131.3***	58.29	68.79***
		(31.18)		
cov11 activity restrictions		-114.9***	72.54	77.85
		(40.26)		
cov14 restrictive covenant		1.630	71.24	73.15
		(31.51)		
cov15 merger restrictions		120.1***	58.03	67.45**
		(27.87)		
Other covenants				
cov4 force majeure		-17.34	7.77	6.71
		(16.56)		
cov5 adverse change		172.0***	0.51	1
		(45.53)		
cov12 coverage ratio		-15.56	0.25	1.68**
		(61.42)		
cov13 fcf to debt service		-10.59	0.51	0.34
		(79.69)		
cov16 sale and leaseback		-29.05**	23.58	44.30***
		(13.94)		
cov18 change of bond terms		-4.213	33.42	14.09***
		(11.89)		

Table continued on next page

Table 6 (continued):
Empirical Model of Excess Spread using Covenant Dummy Variables

VARIABLES	(1) Baseline with covscore	(2) Covenants used as dummies	(3) Frequency PPB in %	(4) Frequency PUB in % (z)
covscore	-32.52***			
	(4.473)			
covscore2	2.749***			
	(0.362)			
rating_score	25.86***	21.01***		
	(4.050)	(4.101)		
leverage	-64.07	-66.84		
	(46.99)	(48.60)		
issue amount (log)	21.91**	31.91***		
	(8.545)	(8.552)		
stock market liquidity	-192.9***	-142.8**		
	(68.43)	(70.78)		
refcorp liquidity	-111.2***	-114.8***		
	(23.90)	(25.54)		
VIX	2.491**	2.582**		
	(1.012)	(1.069)		
benchmark interest rate	-22.77***	-27.56***		
	(6.502)	(6.569)		
yield curve slope	-3.857	-4.063		
	(8.074)	(8.178)		
GDP growth (360d)	-27.73**	-26.55**		
	(11.88)	(12.04)		
MSCI industry return (180d)	-0.0998	0.135		
	(0.491)	(0.484)		
rule of law	-24.72***	-23.78***		
	(8.371)	(8.004)		
top tier arranger	1.226	-5.791		
	(9.772)	(9.749)		
age (log)	-39.34***	-35.62***		
	(13.07)	(13.52)		
assets (log)	-41.64***	-48.09***		
	(6.654)	(6.760)		
profitability	-118.2***	-120.5***		
	(32.28)	(33.12)		
bond maturity	1.262**	2.022***		
	(0.553)	(0.584)		
stock listing	-67.34***	-57.79***		
	(22.18)	(21.49)		
rating_score * time	-0.235	-0.351		
	(0.271)	(0.294)		
placement	4.615	-2.570		
	(11.63)	(11.44)		
Constant	671.0***	707.0***		
	(106.7)	(104.9)		
Observations	684	684	684	684
Adjusted R-squared	0.714	0.737		
Benchmark industry	Industrials	Industrials		
F	59.04	50.60		

Table 7: Use of Covenants and Spread in States of High (Low) Economic Uncertainty

This table reports the estimates from the cross-sectional regressions of spread on a set of variables as reported earlier for the full sample in specification (1), a period of high economic uncertainty in specifications (2) through (7) and for private and public bonds. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Robust standard errors in parentheses. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	baseline	covenant intensity	covenant intensity	covenant intensity	factors	factors	factors
	as in Table 4 specification (8)	high uncertainty	high uncertainty	high uncertainty	high uncertainty	high uncertainty	high uncertainty
Panel A	all bonds	all bonds	PPB	PUB	all bonds	PPB	PUB
covenant score	-32.52***	-22.00***	-16.40**	-33.14**	-9.923	-11.55	-6.871
[factors in (5)-(7)]	(4.473)	(5.445)	(6.955)	(14.13)	(19.29)	(31.87)	(24.62)
covenant score squared	2.749***	1.756***	1.262***	2.866**	41.37***	27.39	37.87
[factors in (5)-(7)]	(0.362)	(0.400)	(0.446)	(1.348)	(15.71)	(22.24)	(25.19)
covscoreXhighuncertainty		-12.99**	-25.21***	2.399	-10.77	-9.592	-24.38
[factors in (5)-(7)]		(5.429)	(7.172)	(12.61)	(19.90)	(32.03)	(26.59)
covscore2Xhighuncertainty		1.229***	2.290***	-0.407	25.20	52.06**	8.720
[factors in (5)-(7)]		(0.470)	(0.553)	(1.322)	(16.51)	(23.37)	(25.95)
Observations	684	684	386	298	684	386	298
Adjusted R-squared	0.714	0.715	0.703	0.750	0.731	0.731	0.757
Benchmark industry	Industrials	Industrials	Industrials	Industrials	Industrials	Industrials	Industrials
All other controls as in Table 4, specification (8)							

Table 8: Pricing Differences between Private (PPB) and Public Placement Bonds (PUB)

This table reports the estimates from the cross-sectional regressions of spread on a set of proxies for credit risk, liquidity, market conditions and firm controls as well as the placement dummy variable as defined in equation (1). The placement variable indicates the excess spread of PPBs over PUBs. The baseline without interaction variables is in specification (1) and uses covscore. Specification (2) adds interactions. Investment and financing factors instead of covscore are used in specification (3), extended by interactions in specification (4). Heteroskedasticity-robust standard errors are in parenthesis. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
	baseline with cov. score	baseline with cov. score + interaction	baseline with cov. factor	baseline with cov. factor + interaction		baseline with cov. score	baseline with cov. score + interaction	baseline with cov. factor	baseline with cov. factor + interaction
constant	671.0***	722.3***	663.9***	657.6***	place*MISCI industry return (180d)		1.943*		2.294**
	(106.7)	(151.4)	(99.78)	(157.1)			(1.033)		(1.096)
placement	4.615	-166	2.931	-129.3	rule of law	-24.72***	-11.54	-23.60***	-13.83
	(11.63)	(208.3)	(11.19)	(208.9)		(8.371)	(13.17)	(7.617)	(13.1)
rating score	25.86***	19.31***	20.96***	19.60***	**covenant score**	-32.52***	-33.36***	-21.14***	-35.89***
	(4.05)	(4.691)	(3.855)	(4.822)	(3: investment covenants)	(4.473)	(8.761)	(5.755)	(11.92)
leverage	-64.07	-7.325	-62.57	1.996	**covenant score squared**	2.749***	2.710***	62.81***	28.01**
	(46.99)	(52.25)	(46.16)	(51.66)	(3: financing covenants)	(0.362)	-0.729	(7.636)	(13.54)
place*leverage		-29.68*		-29.91*	place*investment covenants		0.451		43.46***
		(15.18)		(15.51)			(0.84)		(16.44)
issue amount (log)	21.91**	26.04***	25.57***	25.94***	top tier arranger	1.226	-10.98	-4.318	-8.177
	(8.545)	(9.919)	(8.072)	(10)		(9.772)	-13.59	(9.432)	(13.68)
stock market liquidity	-192.9***	-203.8**	-168.5**	-215.5**	age (log)	-39.34***	-67.07***	-36.76***	-63.12***
	(68.43)	(103.5)	(67.97)	(99.79)		(13.07)	-20.82	(12.69)	(21.79)
Refcorp liquidity	-111.2***	-141.5***	-108.3***	-133.2***	assets (log)	-41.64***	-52.63***	-44.08***	-52.96***
	(23.9)	(29.99)	(24.43)	(31.02)		(6.654)	(8.288)	(6.237)	(8.074)
place*Refcorp liquidity		109.2**		46.55	place*assets (log)		23.94**		19.15*
		(49.37)		(51.88)			(11.1)		(11.43)
VIX	2.491**	1.063	3.009***	1.252	profitability	-118.2***	-237.3***	-132.0***	-242.5***
	(1.012)	(1.284)	(1.002)	(1.24)		(32.28)	(78.35)	(31.89)	(81.01)
place*VIX		4.013**		3.911*	place*profitability		150.7*		186.5**
		(1.997)		(2.095)			(84.43)		(90.47)
benchmark interest rate	-22.77***	-21.67**	-25.57***	-25.48***	bond maturity	1.262**	1.896**	1.861***	2.216***
	(6.502)	(9.196)	(6.525)	(9.104)		(0.553)	(0.786)	(0.575)	(0.789)
yield curve slope	-3.857	-11.16	1.058	-4.797	stock listing	-67.34***	-35.92	-67.33***	-38.56
	(8.074)	(10.46)	(7.957)	(10.44)		(22.18)	(35.8)	(20.84)	(35.4)
place*slope		28.12*		23.5	credit score * time	-0.235	0.107	-0.172	0.206
		(16.46)		(16.77)		(0.27)	(0.34)	(0.27)	(0.35)
GDP growth (360d)	-27.73**	-15.11	-25.48**	-13.39					
	(11.88)	(16.97)	(11.49)	(17.1)	Observations		684		684
MSCI industry return (180d)	-0.0998	-0.742	0.168	-0.533	Adjusted R-squared		0.724		0.728
	(0.491)	(0.652)	(0.482)	(0.693)	F		39.84		43.36

Table 9: Excess Spread of Private Placement Bonds (PPB) in Times of Financial Crisis

This table reports the estimates from the cross-sectional regressions of spread on a set of proxies for credit risk, liquidity, market conditions and firm controls as well as the placement dummy variable as defined in equation (1) during times of financial crisis as defined in other empirical studies and indicated in the text. Effects of the Global Financial Crisis (GFC) and the European Debt Crisis (EDC) using investment and financing factors are measured. The placement variable indicates the excess spread of PPBs over PUBs. Interaction terms are indicated by "X_pl". Heteroskedasticity-robust standard errors are in parenthesis. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

						Continued					
	(1)	(2)	(3)	(4)	(5)		(1)	(2)	(3)	(4)	(5)
	prior to GFC	During GFC	After end of GFC	During EDC	After end of EDC		prior to GFC	During GFC	After end of GFC	During EDC	After end of EDC
		04_2007 - 09_2009	10_2009	03_2010 - 03_2012	03_2012			04_2007 - 09_2009	10_2009	03_2010 - 03_2012	03_2012
constant	691.1***	674.5***	662.8***	669.2***	695.7***	VIX	2.791***	2.697***	3.095***	2.579**	1.957*
	(103.30)	(100.50)	(100.90)	(99.16)	(105.40)		(1.02)	(1.02)	(1.01)	(1.01)	(1.14)
placement	-7.935	4.328	26.4	-9.72	29.28*	benchmark interest	-23.75***	-32.64***	-30.48***	-25.34***	-33.72***
	(11.82)	(11.98)	(18.59)	(11.85)	(14.96)		(6.38)	(7.44)	(7.64)	(6.55)	(7.75)
gfc_prior	-82.14***					yield curve slope	-6.481	4.415	4.286	-1.343	-2.974
	(26.39)						(8.48)	(8.05)	(9.03)	(8.28)	(7.99)
gfcprior_pl	49.41					GDP growth (360d)	-25.35**	-23.38**	-25.39**	-18.03	-16.77
	(30.18)						(11.89)	(11.70)	(11.39)	(12.55)	(11.71)
gfc_during		46.75**				MSCI industry retu	0.335	0.395	0.304	0.118	0.134
		(19.34)					(0.50)	(0.50)	(0.50)	(0.48)	(0.49)
gfcduring_pl		-2.564				rule of law	-23.01***	-24.16***	-23.51***	-22.18***	-21.57***
		(23.75)					(7.92)	(7.59)	(7.72)	(7.75)	(7.82)
gfc_after			-8.907			investment covena	-22.86***	-20.83***	-20.72***	-22.00***	-22.37***
			(24.46)				(5.76)	(5.79)	(5.75)	(5.76)	(5.67)
gfcafter_pl			-33.8			financing covenant	65.08***	63.98***	64.83***	60.00***	62.59***
			(21.32)				(7.56)	(7.60)	(7.68)	(7.59)	(7.49)
edc_during				-12.56		top tier arranger	-3.32	-6.24	-5.825	-0.882	-1.203
				(19.89)			(9.40)	(9.50)	(9.45)	(9.57)	(9.32)
edcduring_pl				52.57**		age (log)	-39.63***	-38.98***	-37.11***	-36.18***	-38.34***
				(24.16)			(12.69)	(12.62)	(12.63)	(12.82)	(12.65)
edc_after					-4.879	assets (log)	-42.45***	-42.40***	-43.11***	-45.60***	-45.79***
					(21.41)		(6.31)	(6.47)	(6.35)	(6.34)	(6.22)
edcafter_pl					-59.85***	profitability	-139.8***	-131.1***	-129.5***	-138.0***	-140.6***
					(18.32)		(31.95)	(31.87)	(32.10)	(32.07)	(32.16)
credit score	25.54***	22.47***	20.53***	20.31***	19.45***	bond maturity	1.646***	2.338***	2.174***	1.808***	2.299***
	(4.34)	(3.98)	(3.86)	(3.94)	(4.00)		(0.57)	(0.62)	(0.63)	(0.58)	(0.63)
leverage	-56.73	-53.33	-60.79	-61	-53.77	stock listing	-65.40***	-68.70***	-67.59***	-71.10***	-67.83***
	(46.41)	(46.27)	(46.28)	(45.83)	(45.87)		(20.82)	(20.75)	(20.76)	(21.26)	(20.71)
issue amount (log)	24.46***	24.96***	26.10***	27.78***	29.53***	credit rating * time	-0.648*	-0.285	-0.0545	-0.145	-0.0359
	(8.06)	(8.03)	(8.03)	(8.02)	(7.95)		(0.35)	(0.27)	(0.29)	(0.27)	(0.28)
stock market liquidity	-181.4***	-150.6**	-141.9**	-182.1***	-161.2**						
	(64.82)	(68.67)	(70.06)	(68.20)	(66.24)	Observations	684	684	684	684	684
refcorp liquidity	-94.52***	-88.29***	-100.8***	-116.0***	-115.2***	≈	0.746	0.745	0.744	0.745	0.748
	(24.13)	(24.28)	(25.42)	(24.71)	(24.68)						

Table 10: Robustness Tests

This table reports a set of robustness tests. Specification (1) is the baseline regression (Table 4, specification 9). Specifications (2) and (3) include 2SLS estimations using instruments assumed to determine covenant intensity in Demiroglu & James (2010). Specification (4) controls for potential endogeneity of bond level controls by excluding them from the used variables. Specification (5) controls for the effect of only including bond contracts for which no covenant information is missing. Specifications (6) and (7) test the impact of exchangeing VIX by other indicators of equity market volatility (VSTOXX, VDAX). Heteroskedasticity-robust standard errors are in parenthesis. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

VARIABLES	(1) Baseline	(2) 2SLS covscore and covscore2 instrumented	(3) f1_mc and f2_loi instrumented	(4) w/o bond level controls	(5) Covenant = 1	(6) VSTOXX	(7) VDAX
rating score	20.96***	18.11***	17.16**	18.94***	20.86***	20.24***	20.15***
	(3.855)	(5.511)	(7.289)	(3.619)	(4.312)	(3.960)	(4.050)
leverage	-62.57			-63.11	-68.35	-56.98	-57.19
	(46.16)			(47.46)	(51.67)	(45.83)	(45.86)
issue amount (log)	25.57***	53.40***	59.04***		16.30*	23.85***	23.77***
	(8.072)	(9.380)	(9.069)		(8.362)	(8.157)	(8.142)
stock market liquidity	-168.5**	-112.1	-96.04	-181.1***	-163.6**	-167.7**	-170.1**
	(67.97)	(91.76)	(89.63)	(67.42)	(68.33)	(68.03)	(68.05)
refcorp liquidity	-108.3***	-121.6***	-136.8***	-117.7***	-117.4***	-121.3***	-126.4***
	(24.43)	(33.68)	(33.35)	(24.63)	(24.91)	(23.43)	(23.36)
VIX (VSTOXX, VDAX)	3.009***	1.882	2.319*	2.877***	2.775***	2.413***	2.348**
	(1.002)	(1.206)	(1.200)	(1.003)	(1.025)	(0.860)	(0.952)
benchmark interest rate	-25.57***	-15.23**	-15.10**	-14.95***	-26.18***	-22.44***	-23.35***
	(6.525)	(6.743)	(6.843)	(4.850)	(6.863)	(6.756)	(6.776)
yield curve slope	1.058	5.313	18.75*	0.796	-2.821	0.0817	1.169
	(7.957)	(10.92)	(10.34)	(7.818)	(8.078)	(7.972)	(7.974)
GDP growth (360d)	-25.48**	-27.11*	-19.80	-23.45**	-21.96*	-25.66**	-27.40**
	(11.49)	(15.57)	(15.84)	(11.76)	(11.67)	(11.55)	(11.64)
MSCI ind. return (180d)	0.168	-0.732	-0.284	0.247	0.0883	0.155	0.117
	(0.482)	(0.537)	(0.500)	(0.485)	(0.490)	(0.457)	(0.448)
rule of law	-23.60***	-40.42***	-34.31***	-24.41***	-19.01**	-22.89***	-22.99***
	(7.617)	(9.915)	(9.523)	(7.491)	(8.271)	(7.587)	(7.573)
investment covenants	**-21.14*** **	**-74.25*** **	**-31.61**	**-19.58*** **	**-17.40** **	**-20.87*** **	**-21.08*** **
	(5.755)	**(25.04)**	**(45.38)**	**(5.735)**	**(8.686)**	**(5.747)**	**(5.755)**
financing covenants	**62.81*** **	**5.711*** **	**54.40** **	**61.78*** **	**70.03*** **	**62.47*** **	**62.65*** **
	(7.636)	**(1.725)**	**(24.13)**	**(7.358)**	**(8.994)**	**(7.631)**	**(7.678)**
top_tier arranger	-4.318	7.603	-1.804		-1.279	-1.936	-2.437
	(9.432)	(14.58)	(13.69)		(9.963)	(9.384)	(9.427)
age (log)	-36.76***			-41.92***	-43.62***	-35.69***	-35.70***
	(12.69)			(12.43)	(15.61)	(12.83)	(12.91)
assets (log)	-44.08***	-43.01***	-53.02***	-34.85***	-35.32***	-44.04***	-43.85***
	(6.237)	(9.588)	(7.868)	(5.282)	(6.535)	(6.289)	(6.280)
profitability	-132.0***	-139.5***	-113.8***	-129.1***	-49.44	-133.9***	-133.3***
	(31.89)	(39.80)	(37.09)	(32.53)	(33.86)	(31.90)	(32.05)
bond maturity	1.861***				2.070***	1.721***	1.790***
	(0.575)				(0.587)	(0.588)	(0.586)
stock listing	-67.33***	-26.18	-43.53**	-63.87***	-93.12***	-69.76***	-68.84***
	(20.84)	(23.30)	(21.75)	(21.27)	(25.39)	(20.73)	(20.77)
credit rating*time	-0.172	0.172	0.312	0.0729	-0.192	-0.131	-0.118
	(0.266)	(0.302)	(0.349)	(0.246)	(0.310)	(0.276)	(0.283)
placement	2.931	-11.37	12.75	9.267	5.347	3.000	2.839
	(11.19)	(20.32)	(18.48)	(10.87)	(11.76)	(11.14)	(11.15)
Constant	663.9***	618.9***	478.8***	719.6***	629.0***	656.5***	660.1***
	(99.78)	(161.5)	(120.4)	(99.71)	(107.3)	(99.36)	(99.45)
Observations	684	747	747	690	600	685	685
Adjusted R-squared	0.742	0.619	0.662	0.726	0.747	0.730	0.729

Table 10: Robustness tests (continued)

This table reports a set of robustness tests. Specification (8) includes a dummy variable for 144A registered bonds, specification (9) shows the results when using only stock listed issuers. In specification (10), accounting conservatism as proxied by the use of General Accepted Accounting Principles (GAAP) of the issuer is included. Specification (11) includes only issuers that use both private and public placements, which we call “switchers”. Finally, in specification (12), year fixed effects are used. Heteroskedasticity-robust standard errors are in parenthesis. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

VARIABLES	(8) A144	(9) listed issuer	(10) switchers	(11) year fixed effects
rating score	20.80***	25.29***	20.66***	22.46***
	(3.984)	(4.920)	(4.525)	(5.307)
leverage	-72.51	-52.40	-10.69	-36.88
	(47.93)	(53.00)	(50.02)	(45.10)
issue amount (log)	25.39***	17.95**	17.58*	25.13***
	(8.276)	(8.680)	(10.42)	(8.295)
stock market liquidity	-143.6**	-124.2*	-252.6***	-123.2*
	(70.78)	(74.55)	(84.37)	(72.25)
refcorp liquidity	-113.2***	-131.1***	-101.6***	-61.89
	(25.34)	(23.82)	(29.31)	(47.64)
VIX (VSTOXX, VDAX)	3.295***	2.301**	2.147*	1.616
	(1.052)	(1.021)	(1.278)	(1.261)
benchmark interest rate	-25.82***	-19.19***	-14.29*	-40.24***
	(6.739)	(6.602)	(7.266)	(10.49)
yield curve slope	-1.188	-4.779	27.46***	9.463
	(8.211)	(8.274)	(7.987)	(18.13)
GDP growth (360d)	-25.43**	-22.04*	-16.62	-56.73***
	(11.85)	(11.87)	(14.35)	(15.24)
MSCI ind. return (180d)	0.294	0.0289	0.322	0.0252
	(0.491)	(0.502)	(0.697)	(0.516)
rule of law	-23.52***	-18.80*	-7.607	-27.33***
	(8.015)	(10.70)	(8.562)	(8.077)
investment covenants	**-22.71*** **	**-25.82*** **	**-29.64*** **	**-20.23*** **
	(7.332)	**(6.243)**	**(6.888)**	**(5.593)**
financing covenants	**62.83*** **	**55.67*** **	**62.51*** **	**67.66*** **
	(8.366)	**(8.644)**	**(7.803)**	**(7.379)**
top_tier arranger	-7.127	4.039	-5.214	7.615
	(9.818)	(9.187)	(10.45)	(10.24)
age (log)	-44.19***	-50.44***	-72.80***	-35.49***
	(15.02)	(14.08)	(20.95)	(12.41)
assets (log)	-43.05***	-36.30***	-23.11***	-48.46***
	(6.409)	(8.083)	(8.406)	(6.618)
profitability	-112.9***	-109.7***	-114.8***	-133.8***
	(35.55)	(30.28)	(29.25)	(31.99)
bond maturity	2.052***	1.556***	1.276*	2.867***
	(0.599)	(0.568)	(0.739)	(0.789)
stock listing	-71.61***		-53.72**	-50.89**
	(23.84)		(25.68)	(21.22)
credit rating*time	-0.141	-0.193	-0.234	-0.635
	(0.281)	(0.302)	(0.306)	(0.512)
placement	6.387	1.949	0.958	-1.718
	(13.33)	(11.61)	(11.69)	(11.07)
a144	-4.971			
	(12.11)			
Constant	666.8***	496.8***	391.5***	796.1***
	(103.1)	(148.1)	(123.4)	(115.4)
Observations	637	614	382	684
Adj. R-squared	0.745	0.740	0.819	0.759

Table 11: Accounting Quality and Conservatism

This table reports the results using the binary choice model as in Table 3 (switcher model) in specifications (1) through (3). The specifications additionally include proxies for accounting quality and conservatism as measured by the use of a specific accounting standard by the issuer (using a dummy variable) such as International Financial Reporting Standards (IFRS), US Generally Accepted Accounting Principles (GAAP) and International Accounting Standards (IAS). The latter includes different European GAAPs, but not IFRS or US GAAP. Based on the findings of Lin et al. (2012) and Barth et al. (2006), US GAAP is considered to proxy for higher accounting quality relative to IFRS and IAS. Specifications (4) through (6) include the baseline regression as in Table 4, specification (8) and using the proxies for accounting quality. The percentage change in odds for a SD increase in X are in parenthesis in specifications (1) through (3). Heteroskedasticity-robust standard errors are in parenthesis in specifications (4) through (6). The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. Coefficients significant at the 1%, 5% or 10% level are market with three, two or one asterisks, respectively. (*** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)	(3)	(4)	(5)	(6)
	Choice Model Including IFRS	Choice Model Including US GAAP	Choice Model Including IAS	Regression Model Including IFRS	Regression Model Including US GAAP	Regression Model Including IAS
IFRS / US GAAP	1.167	0.599	1.411	39.66***	-29.34**	12.81
	(0.314)	(0.204)	(0.539)	(9.954)	(13.89)	(24.07)
rating score	0.906	0.888	0.899	27.28***	25.77***	25.62***
	(0.0747)	(0.0753)	(0.0752)	(4.076)	(4.094)	(4.090)
leverage	0.394	0.524	0.382	-57.62	-58.39	-65.05
	(0.403)	(0.560)	(0.388)	(47.16)	(47.61)	(47.34)
issue amount (log)	1.957***	2.042***	1.947***	23.80***	23.13***	21.80**
	(0.421)	(0.448)	(0.417)	(8.328)	(8.429)	(8.508)
stock market liquidity	0.0426	0.0367*	0.0444	-216.2***	-188.4***	-188.5***
	(0.0841)	(0.0725)	(0.0873)	(68.59)	(68.89)	(69.36)
refcorp liquidity	0.388	0.415	0.361	-103.8***	-112.2***	-113.1***
	(0.248)	(0.267)	(0.230)	(24.20)	(24.20)	(23.70)
VIX (VSTOXX, VDAX)	0.886***	0.891***	0.888***	2.329**	2.499**	2.524**
	(0.0248)	(0.0247)	(0.0253)	(1.000)	(1.012)	(1.013)
benchmark interest rte	1.643***	1.611**	1.665***	-24.27***	-22.51***	-22.58***
	(0.312)	(0.311)	(0.312)	(6.471)	(6.579)	(6.577)
yield curve slope	1.670**	1.695**	1.580**	0.495	-3.530	-4.608
	(0.367)	(0.364)	(0.342)	(8.138)	(8.029)	(8.233)
GDP growth (360d)	1.127	1.098	1.080	-26.32**	-27.21**	-27.54**
	(0.371)	(0.356)	(0.362)	(11.80)	(11.89)	(11.85)
MSCI ind. return (180d)	0.960***	0.964***	0.962***	-0.0438	-0.0439	-0.0810
	(0.0118)	(0.0121)	(0.0120)	(0.489)	(0.487)	(0.489)
rule of law	0.543**	0.543*	0.546**	-23.47***	-25.51***	-24.67***
	(0.169)	(0.171)	(0.164)	(8.430)	(8.379)	(8.342)
covenant score				**-31.97***	**-32.25***	**-32.14***
				(4.460)	**(4.458)**	**(4.484)**
covenant score squared				**2.670***	**2.729***	**2.724***
				(0.360)	**(0.361)**	**(0.362)**
top_tier arranger	3.043***	3.006***	3.076***	2.863	2.515	1.141
	(0.795)	(0.787)	(0.800)	(9.694)	(9.758)	(9.790)
age (log)	1.506	1.576	1.381	-42.03***	-41.05***	-39.47***
	(0.571)	(0.601)	(0.525)	(12.80)	(12.93)	(13.05)
assets (log)	0.721**	0.687**	0.732**	-42.46***	-42.87***	-41.64***
	(0.115)	(0.115)	(0.112)	(6.617)	(6.626)	(6.634)
profitability	0.282	0.525	0.398	-127.8***	-115.8***	-114.3***
	(0.391)	(0.689)	(0.568)	(33.16)	(32.52)	(32.96)
bond maturity	0.971	0.972	0.971	1.277**	1.309**	1.267**
	(0.0203)	(0.0205)	(0.0205)	(0.556)	(0.552)	(0.552)
stock listing	1.856	1.827	1.920	-65.29***	-64.54***	-66.46***
	(1.030)	(1.032)	(1.061)	(21.77)	(22.13)	(22.49)

Table 11 (continued)

credit rating*time	1.026***	1.026***	1.027***	-0.387	-0.228	-0.195
	(0.00605)	(0.00610)	(0.00626)	(0.266)	(0.275)	(0.291)
placement				3.709	1.426	4.992
				(11.43)	(11.61)	(11.67)
Constant	9.734	12.25	8.181	645.0***	688.8***	666.8***
	(38.19)	(48.96)	(31.23)	(107.1)	(107.3)	(106.3)
Observations	382	382	382	684	684	684
(Pseudo) Adj. R^2	.194	0.198	0.198	0.721	0.716	0.714

Appendix Table I: Correlation Matrix[1]

	spread	maturity	amount	top_tier	covscore	log_age	logsize_assets
spread	1						
maturity	-0.2042	1					
amount	-0.1892	0.1407	1				
top_tier	-0.0546	-0.0344	0.1134	1			
covscore	0.1238	0.013	0.1167	0.1349	1		
log_age	-0.3319	0.1587	0.0885	0.1209	-0.0745	1	
logsize_assets	-0.5955	0.2059	0.3985	0.0972	-0.1214	0.4181	1
logsize_revenues	-0.5872	0.2185	0.374	0.088	-0.0717	0.4784	0.9189
leverage	0.3005	-0.106	-0.0225	0.0368	0.0772	-0.2702	-0.3103
listed	-0.3334	0.1386	0.1945	0.1048	0.1143	0.2381	0.3392
profit	-0.188	0.0329	0.1187	0.0627	0.0439	0.1038	0.1409
rating_score	0.6717	-0.203	-0.272	-0.0831	0.0548	-0.4012	-0.7432
gdp_360	-0.0298	-0.029	0.0756	-0.0312	-0.0657	-0.0831	0.0207
mscii_180	-0.034	-0.045	0.034	0.028	0.1399	-0.157	-0.151
msciitot_180	0.0187	-0.0908	-0.0072	0.0048	0.1362	-0.258	-0.1954
slope	0.1634	-0.0382	-0.0302	-0.0128	0.106	0.0599	0.0788
benchmark	-0.2109	0.3984	-0.0056	-0.0941	-0.0908	-0.0304	-0.093
bml_refcorp	-0.1414	-0.0614	-0.0325	0.018	0.0045	-0.1604	-0.2
eml	-0.0112	-0.0466	0.0062	0.0245	0.1348	-0.0856	-0.0827
vix	0.0597	0.0779	-0.0015	-0.0265	-0.0869	0.1488	0.1663
rolscore	-0.0724	-0.0167	0.0312	0.1191	-0.0329	-0.0241	-0.0392

	logsize_revenues	leverage	listed	profit	rating_score	gdp_360	mscii_180
logsize_r	1						
leverage	-0.3951	1					
listed_com~d	0.3284	-0.2968	1				
profitw	0.1903	0.0336	-0.0589	1			
rating_score	-0.7451	0.5088	-0.2526	-0.2846	1		
gdp_360	-0.0508	-0.0107	-0.0478	-0.0576	0.0446	1	
mscii_180	-0.1647	0.0738	-0.0274	-0.0537	0.1403	0.1308	1
msciitot_180	-0.2126	0.1332	-0.0797	-0.049	0.1856	0.2521	0.7944
slope	0.02	0.0386	0.0949	-0.0142	0.0133	-0.0306	-0.0644
benchmark	-0.0699	-0.0339	-0.068	-0.0557	0.0422	0.0519	0.0428
bml_refcorp	-0.1835	0.0938	-0.111	-0.043	0.1714	0.2179	0.3898
eml	-0.0729	0.039	0.0544	0.0241	0.0361	-0.0758	0.3351
vix	0.1747	-0.1127	0.1082	0.0023	-0.1375	-0.164	-0.58
rolscore	0.0235	0.0108	-0.02	-0.031	-0.0887	-0.0103	0.083

	msciitot_180	slope	benchmark	bml_refcorp	eml	vix	rolscore

Appendix Table I (continuted)

msciitot_180	1						
slope	-0.0582	1					
benchmark	0.0008	-0.3877	1				
bml_refcorp	0.4986	-0.4367	0.2529	1			
eml	0.4044	-0.0279	-0.0945	0.2516	1		
vix	-0.6986	0.2627	-0.0088	-0.7049	-0.3798	1	
rolscore	0.0547	-0.0482	-0.0246	0.0364	0.0106	-0.0424	1

[1] Pearson product-moment correlation coefficients

Appendix Table 2: Riskadjusted Excess Spreads of Private Placement Bonds (PPB) by Issuer Domicile

This table presents risk adjusted spreads (residuals) from the postestimation of an OLS regression of spread on credit risk. Bivariate comparisons of observed and estimated riskadjusted spreads of private bonds and pubilc bonds from 2002 through 2015, sorted by the main issuer domiciles observed in the sample, that is for domiciles with at least 20 PPB observations. Regressing spread on rating score renders an adjusted R2 of 40.35% with t = 43.4, p<0.001 for rating score and a constant of -160.85 (t=-14.77). The coefficient is 49.06 and indicates the increase in spread per one unit change in rating score (with min. = 1 and max. = 18). The mean residuals values of PPB (r_ppb) and PUB (r_pub) indicate excess spread after correcting for credit risk as measured by credit score. The difference between r_ppb over r_pub is indicated

By Issuer Domicile

	All	Private Placement Bonds (PPB)			Public Placement Bonds (PUB)			PPB vs. PUB	
	n Bonds	n Bonds	Observed Spread	Mean Residuals	n Bonds	Observed Spread	Mean Residuals	Δ mean Residuals	t-value
			(s_ppb)	(r_ppb)		(s_pub)	(r_pub)	(r_ppb - r_pub)	
France	135	90	283.81	-23.39	45	283.13	-28.75	5.37	0.23
Ireland	97	41	245.47	-40.96	56	173.85	-59.73	18.76*	0.86
Luxembourg	85	54	491.30	65.09	31	473.38	51.23	13.85	0.38
Netherlands	60	44	419.23	-33.64	16	340.18	-5.05	-28.58	0.63
United Kingdom	240	152	374.51	28.75	88	225.90	-74.66	103.41***	5.20

in the row "Δ mean residuals" together with Wilcoxon rank sum test results. T-values from a student t-test are in the next row. Two tailed statistical significance is denoted ***, ** , and * / at the 1 %, 5 % and 10 % level respectively.

9. Appendices

Appendix A: Creditmodel Corporates 2.6 of S&P Global Market Intelligence

Appendix B: Variable Definitions

Appendix C: Description of Debt Covenants

Appendix D: Factor Analysis

Appendix A Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence

The following description of CreditmodelTM Corporates 2.6 (CM) is based on the S&P Global Market Intelligence technical note describing the short form credit scoring model (August 2016). A more comprehensive unpublished technical reference guide is available from S&P Global Market Intelligence.

Overview: [CM is] a statistical model trained on credit ratings from S&P Global Ratings. [CM] is a widely used statistical tool that facilitates [the] evaluation of a company's credit quality by generating rating scores [from aaa, with a numerical value of 1, to ccc or lower, with a numercal value of 18] for both public and private corporates globally. [It] utilizes both financial data from corporates and the most relevant macroeconomic data, to generate a quantitative rating score that statistically matches a credit rating issued by S&P Global Ratings. S&P Global Ratings does not contribute to or participate in the creation of rating scores generated by S&P Global Market Intelligence. Lowercase nomenclature is used to differentiate S&P Global Market Intelligence PD credit model scores from the credit ratings issued by S&P Global Ratings. [CM] covers both privately held and publicly listed corporates. The model's primary output is a lower-case letter grade score. [It provides users] with access to estimates of creditworthiness for more than 48,0003 non-financial corporations globally, spanning more than 10 years, based upon S&P Capital IQ's database of public and private company fundamentals.

Trained on S&P Global Ratings credit ratings and S&P Capital IQ Platform's Financial Data: [CM] uses more than 10 years of S&P Global Ratings' historical ratings for corporate companies. [CM] uses standalone credit profiles (SACP) where available, or strippes any group or parental support from the final rating if the standalone credit profile is unavailable, in order to obtain the credit profile of a company prior to any extraordinary support considerations. [CM] uses more than 52,000 observations globally [and more than 8'500 for Europe] for corporates, that [were] complemented with internal standalone assessments generated for companies operating in emerging markets to enrich [the] training dataset. [S&P] collected all relevant financial items for the same companies, from the S&P Capital IQ Platform standardized fundamentals.

Appendix A Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

Systemic Risk Data: [Context was considered when developing the] model [by considering] credit ratings by S&P Global Ratings via the Corporate Industry and Country Risk Assessment (CICRA). A CICRA is a combination of country risk and industry risk. Country risk refers to the risk associated with investing in a country. It is a broad and general term that represents risks linked to changes in the business environment that may adversely affect operating profits or the value of assets in a specific country. This type of risk affects all companies operating within a particular country and is a blend of monetary factors (e.g., currency control), political factors (e.g., civil war), and operating factors (e.g., corruption). For Country Risk, S&P Global Market Intelligence has developed a quantitative model that generates Country Risk Scores that closely align with S&P Global Ratings' assessments, and expands the coverage to 247 countries worldwide by establishing a "proxy mechanism" based on geographic proximity considerations, regional influences, independence (or not) of the central banks, the degree and evolution of a count ry's economic development and financial regulatory environment and its type of political system. Industry risk is usually determined by elements such as barrier to entry, ease of conversion, level of competition, market fragmentation, etc. This is implicitly captured in CM2.6 by training industry-specific sub-models or adding dummy variables to reflect differences in specific industry sectors.

Variable Selection Process: [CM tested] more than 100 alternative financial and non-financial items, in order to investigate the most predictive variables for modelling purposes [and] applied a vigorous, cutting-edge procedure for the variable selection process that helps to prescreen what could be included as an input for the model. In order to select the final set of inputs and variables we used both statistical analysis and business judgment to weight the following considerations: [a.] Availability of Factors: All factors included in the model must be widely available on a consistent basis over time for companies in each sector. Some factors have a high predictive power but are seldom reported by companies (e.g. some cash flow items of private corporates); while these factors may help boost a model's performance, such a model would be irrelevant for

Appendix A Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

firms that do not report similar information. [b.] Correlation: Highly correlated factors do not provide additional insights and could distort model performance. [CM] used correlation analysis to identify and remove correlated variables. [c.] Representation of All Relevant Risk Dimensions: In order to capture the variety of factors that influence the creditworthiness of corporates, [CM] referred to the list of “risk dimensions” that S&P Global Ratings uses for the analysis of corporate firms, and classified each candidate variable into its corresponding risk dimension, using expert judgement. Then, [CM] selected the variables that would comprise these risk dimensions from a range of categories, including financial information, as well as economic and industry-based risk indicators to ensure a proper balance of microeconomic and macroeconomic factors, similar to how a credit analyst would analyze a corporate company. [CM controls for] potential differences in the explanatory power of factors in different industries, where relevant [and] early warning signals such as low values of Debt / Capital. [According to the technical reference guide, p. 33, CM applies the following variables for European corporates: total assets to represent the company size effect, return on capital to reflect profitability, cash from operations interest coverage to account for debt service capability, asset turnover to reflect efficiency, debt / debt + equity to represent gearing, free operating cash flow / debt to calculate debt service capability, operating income before depreciation and amortisation to reflect profitability and long term liability / equity to again reflect gearing.]

Regional and Sector Segmentation: In order to achieve optimal model performance and stability of the results, CM2.6 was trained using a regional/sector segmentation based on similarities of available financials and rating distributions, as well as taking into account data availability and other macroeconomic considerations. Europe was trained with 10 sub-regions based on the ratings distribution [and] 19 industry sector dummy variables. Finally, the airlines industry was treated as a separate, global model due to the globalized nature of this industry. More details can be found in the technical reference guide.

Appendix A Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

Methodology Most of the models available in the market only employ simple logistic regression techniques. [The CM] model employs an advanced generalization of the logistic regressions, based on the family of Exponential Density Functions. It uses the prior distribution of all S&P Global Ratings credit ratings in the training dataset as an "anchor distribution", and modifies it in proportion to how much the financials of a specific company deviate from those of companies used in the anchor distribution. The process of variable selection considers both linear terms and terms of higher order, and selects the final variables according to k-fold Greedy Forward Approach, a widely-used statistical method that ensures a good fit out-of-sample and out-of-time. The model uses a number of techniques, including variable t ransformations, which minimize the impact of extreme values. It also uses various constraints, which avoid risk of model over-fitting without any loss of data as well as a more accurate estimation of the parameters and final output. The model maximizes the maximum likelihood function within a Maximum Expected Utility, adapted to a multi-state case (the rating categories, on which the model is trained, are not binary, but 18 in total), and uses the Akaike Information Criterion (AIC) to limit the maximum number of variables that are included (model parsimony). This optimization process ensures the model exhibits greater stability and out-of-time performance. Monotonicity constraints are applied to ensure that the model produces outputs that follow economic intuition.

Annual Model Validation Since the release of CM2.6 in 2013, S&P Global Market Intelligence has conducted a detailed performance evaluation annually, based on the actual performance data and provided the results of the validation to users. If a significant deterioration in model performance is observed, S&P Global Market Intelligence will consider a recalibration of the parameters or a review of the risk drivers. [The CM performance is measured in percent of exact matches, +/- 1 notch, +/- 2 notches and +/- 3 notches deviation from the S&P Global Ratings. The last available validation was done in July 2016 and has resulted in 22% exact matches, 56 % matches within 1 notch, 78 % within 2 notches and 88 % within 3 notches.]

Appendix B Variable definitions

Dependent variable

spread — is the dependent variable calculated as the difference between the yield on a corporate fixed coupon bond calculated as internal rate of return (IRR) and the yield of the riskless maturity matched government bond on the issue date. Benchmark bonds are the Constant maturity treasuries.

Credit risk proxies

rating score — is a score with a numerical value of 1 (AAA) to 18 (CCC) proxying for credit rating with credit model 2.6 of S&P Global Market Intelligence (Standard & Poors, 2016). The score represents a company's standalone credit risk and is based on a statistical tool trained on S&P Global Ratings for assessing credit risk of corporates. See more detailed description Appendix A.

leverage — is book leverage calculated as the ratio of total long-term debt to total assets of the issuer. Most recent financial data preceding the bond issue from S&P is used. Leverage is winsorised at the 1%-level to correct for extreme outlier values in the data set.

Liquidiy proxies

issue amount — is the issue amount of a bond / logarithm of the issue amount. Data is from S&P and verified with Bloomberg.

refcorp liquidity — Bond market liquidity measures the yield to maturity spread between the 7 year riskless Refcorp agency bonds (Resolution Funding Corporation, a US government agency) versus the 7 year yield to maturity on the benchmark bonds as defined in Appendix B for USD denominated bonds at the issue date.

stock market liquidity — is the monthly aggregate liquidity measure of Pástor & Stambaugh (2003). It provides a monthly cross-sectional average of individual stock liquidity measures and indicates volume-related return reversals arising from liquidity effects. The aggregate average market liquidity of the month prior to the bond issue is matched with each issue date. Data are from Wharton research data services (wrds) platform (https://wrds-web.wharton.upenn.edu/wrds/).

Appendix B Variable definitions (continued)

Agency cost proxies

covenant score	measures the covenant intensity and describes the number of covenants included in a bond. The score is the sum of eighteen single covenants, takes a minimum value of 0 and a maximum value of 18. A detailed description of these 18 covenants is in Appendix C. Data are from Bloomberg.
investment covenants	is a combination of covenants, based on factor analysis that mainly consist of covenants restricting investments and asset sales.
financing covenants	is a combination of covenants, based on factor analysis that mainly consist of covenants restricting the obtaining of new financing.
top tier	indicates whether a bond issue was placed by a top tier arranger, being a bank or securities dealer. If one of the three biggest European arrangers in the calendar year prior to a bond issue, measured by it's annual placement volume, was a member of the syndicate, this dummy variable takes the value of one, zero otherwise. Data are from Bloomberg.
age	is the age of the issuer, defined as the number of years since inception to the bond issue date.

Market condition proxies

gdp	is the real GDP growth rate for a period of 360 ("gdp_360") calendar days prior to a bond issue. Data is from European GDP data from Eurostat (http://ec.europa.eu/eurostat/web/national-accounts/data/main-tables adjusted for inflation given by the Harmonised Index of Consumer Prices (HICP) oft he Euro area compiled by Eurostat and the national statistical institutes. Details can be retreived from http://ec.europa.eu/eurostat/web/hicp/data/database.
yield curve slope	is the difference between the 10-year and 2-year benchmark rates are used to account for the level and the slope of the yield curve.

Appendix B Variable definitions (continued)

benchmark — is the risk-free rate (benchmark interest rate) as described in Appendix A to account for the level of the risk-free-rate.

vix — are the CBOE VIX-index values. They correspond to a weighted average of eight implied volatilities of near-the-money options on the OEX (S&P 100–Index). Data are from Bloomberg. As a second indicator of aggregate equity market volatility We consider VSTOXX (“vstoxx”), an index jointly developed by the German Stock Exchange and Goldman Sachs to measure volatility in the Eurozone. VSTOXX is based on the EURO STOXX 50 Index options traded on Eurex. It measures the implied volatility on options with a rolling 30 day expiry. We also use VDAX-Index (“vdax”), which is the German counterpart to the VIX index for the S&P 500. Data are from Bloomberg.

MSCI — is used to measure the return of the index representing the issuer’s industry. We use the Morgan Stanley Capital Index (MSCI) Europe Index family and its industry specific derivatives matched by GICS-codes to calculate these returns for a period of 180 days preceding a bond issue. Data are from Bloomberg. It is also used to measure the Morgan Stanley Capital Index (MSCI) overall index return (not industry specific) over the past 180 or 360 days prior to a bond issue. We use Europe wide stock returns.

rule of law — is the rule of law score developed by Kaufmann et al. (2010). It measures the enforcement environment in the issuer domicile country. Higher scores equate to a higher quality enforcement environment. Rule of Law is one of six dimensions measured within the Worldwide Governance Indicators project of the World Bank, covering 200 countries since 1996. The six governance indicators are based on different data sources including commercial business information providers, public sector data providers as well as non-governmental organization data providers and survey providers. A more comprehensive description is available on www.govindicators.org

<u>Control Variables</u>

assets — measure the size of an issuer firm measured by (the logarithm of) total assets or the total

revenues — revenues of the issuer. The data are from S&P.

Appendix B Variable definitions (continued)

maturity — is a bond's years to maturity. The data are from S&P.

stock listing — is a dummy variable indicating whether the issuer or its parent company is a listed company. A firm is considered to be listed if Bloomberg indicates a market capitalization value on the issue date of a bond considered in the sample.

profitability — is the profitability of a firm gauged by the ratio of EBIT to revenues. The data is from S&P. Profit is winsorised at the 1%-level to correct for extreme outlier values in the data set.

industry — is a dummy variable taking the value of one, if an issuer is affiliated to a certain industry defined by the Global Industry Classification Standards (GICS) codes, zero otherwise. The benchmark industry is "industrials". The data is from S&P.

country — is a dummy variable for issuer domicile, taking the value of one if an issuer has it's domicile in a specific country, zero otherwise, the UK being the benchmark issuer domicile. The data is from S&P.

time — is a time index dummy variable, equal to 0 in 2002 and increasing by 1 every year thereafter to control for potential structural changes over time.

A144 — indicates whether a bond is registered under SEC Rule 144A or not. A dummy variable taking the value of 1, zero otherwise, is used.

<u>Embedded options</u>

options — is a dummy variable taking the value of one, zero otherwise, if a call, whole call, put, control put or rating related put (all options described below) is attached to a bond issue

call — indicates whether a bond is subject to early redemption through a call provision (excluding make-whole call redemptions).

Appendix B Variable definitions (continued)

call_whole	indicates a provision that allows a borrower to prepay the remaining fixed rate term, making an additional payment that is derived from a formula based on the net present value of future debt payments.
put	indicates a standard put option and identifies a bond that is putable.
put_control	indicates a rating trigger provision, giving the bondholder the right to execute a put, if the bond falls below a designated credit rating, usually investment grade.
put_rating	indicated a provision which allows for the redemption of the bonds in the event of a corporate takeover or merger etc.

Appendix C Description of Debt Covenants

The following table provides an overview of all covenant variables and their Bloomberg definitions.

Variable	**Covenant**	**Bloomberg definition**
cov1	Restricted payments	Indicates a negative or restrictive covenant that limits an issuer's ability to make distributions, whether in the form of cash, assets or securities to shareholders, to redeem subordinated debt, repurchase equity or provide dividends.
cov2	Financial Statements	Indicates the existence of an affirmative or restrictive covenant requiring the borrower to deliver to lenders periodic financial statements.
cov3	Default Info available	Indicates whether covenant/default information is available.
cov4	Force Majeure	Indicates a clause that allows the underwriter to cancel the issuance of the bond should certain events occur.
cov5	Material Adverse Change Clause	Indicates a covenant or clause in the loan documentation which is triggered by an event, condition or change which materially and adversely affects, or could reasonably be expected to materially and adversely affect, a company's financial results, financial condition, business, or prospects.
cov6	Negative Pledge Clause	Indicates a covenant in the credit agreement whereby the company is prohibited from pledging or placing liens on certain assets.
cov7	Limit of Indebtedness	Indicates a negative or restrictive covenant that places limitations on the amount of debt that the issuer can incur. This can be expressed as a percentage of assets or in monetary terms.
cov8	Cross Default	Indicates a stipulation stating that if an issuer is in default on other borrowings, such non-payment is also considered default in respect to the issue with the cross default covenant.
cov9	Negative Covenant Indicator	Indicates a restrictive bond clause intended to prevent a corporation from giving benefits to the shareholders at the expense of the bondholders.
cov10	Sales of Assets Restriction	Indicates a negative or restrictive covenant that limits the ability of the issuer to sell any or all of its assets.
cov11	Restriction on Activities	Indicates a negative covenant that can apply to any restrictions on the business activities of the issuer.

Appendix C Description of Debt Covenants (continued)

cov12	Debt Service Coverage Ratio	Indicates cash available for debt service/total or senior debt service. In corporate finance, it is the amount of cash flow available to meet annual interest and principal payments on debt, including sinking fund payments.
cov13	Free Cash Flow to Debt Service	Indicates if the issuer has supplied specific ratios and has pledged to maintain these ratios throughout the life of the bond.
cov14	Restrictive Covenant Indicator	Indicates any pledge made by the issuer to refrain from an activity that will be considered detrimental to the bondholders.
cov15	Merger Restrictions Covenant Indicator	Indicates a negative or restrictive covenant placed on the issuer which states that the issuer may not merge or consolidate with any other entity without satisfying certain conditions.
cov16	Limitation on Sale and Leaseback	Indicates a restrictive or negative covenant that prevents the issuer from selling assets (or removing them from the balance sheet for accounting purposes) then leasing them back from the company to which they were sold.
cov17	Limitation on Subsidiary Debt	Indicates a negative or restrictive covenant that places limitations on the amount of debt that the issuer's subsidiaries can incur. This can be expressed a as percentage of assets or in monetary terms.
cov18	Collective Action Clause	Indicates an additional covenant clause designed to give a supermajority of bondholders (usually 66.66% or 75%) the ability to consent to changes in the fundamental terms of **the** bond.

Appendix D Factor Analysis

This Appendix shows the results of the factor analysis using the covenants described in Appendix C. Panel A depicts the principal factors and their eigenvalues. Panel B includes the rotated factor loadings, unique variances together with the Kaiser-Meyer-Olkin measure of sampling adequacy.

Panel A Principal Factors and Eigenvalues

Factor analysis/correlation		Number of obs =	1,220
Method: principal factors		Retained factors =	2
Rotation: orthogonal varimax (Kaiser off)		Number of params =	35

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	6.28119	2.85744	0.5754	0.5754
Factor2	3.42375	.	0.3136	0.8890

LR test: independent vs. saturated: chi2(153) = 2.3e+04 Prob>chi2 = 0.0000

Panel B Rotated factor loadings (pattern matrix), unique variances and Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	Factor1	Factor2	Uniqueness	Variable	kmo
cov1		0.8932	0.1455	cov1	0.8944
cov2	0.4729	0.5751	0.4456	cov2	0.9560
cov3	0.6672		0.5327	cov3	0.9862
cov4			0.9416	cov4	0.8886
cov5			0.9879	cov5	0.5168
cov6	0.8817		0.1759	cov6	0.9273
cov7		0.9195	0.1014	cov7	0.8351
cov8	0.6816	0.3213	0.4322	cov8	0.9631
cov9	0.9483		0.0838	cov9	0.8525
cov10	0.7747	0.4040	0.2367	cov10	0.8541
cov11	0.9457		0.0626	cov11	0.9267
cov12			0.9864	cov12	0.5479
cov13			0.9923	cov13	0.5208
cov14	0.9490		0.0825	cov14	0.8566
cov15	0.7705	0.3814	0.2609	cov15	0.8564
cov16	0.4368		0.8079	cov16	0.8711
cov17		0.8808	0.1660	cov17	0.8762
cov18	0.3080		0.8533	cov18	0.9218
				Overall	0.8901

(blanks represent abs(loading)<.3)

Chapter II

The Valuation Effects of Private Placements of Straight Bonds

Pascal Böni[28]

Abstract

This study examines how the use of restrictive covenants impacts shareholder wealth *ex ante* and in the context of issuing privately placed bonds. I identify a specific channel, namely the use of restrictive covenants, through which firm value is affected *ex ante*. Stock price effects appear to be driven by the use of covenants rather than by the type of security sold to investors. For an event window of -10;+30 days around the announcement of issuing privately placed bonds, the cross-sectional abnormal return increases with the number of restrictive covenants attached to bonds. For firms issuing private placement bonds with average covenant intensity, the abnormal return amounts to a mean (median) of -5.3% (-4.3%) or 44% of the new funds raised. Negative abnormal returns become even larger when limiting a firm's flexibility to raise additional debt in the future, i.e. for bond issues with additional debt covenants attached. In contrast, abnormal returns are statistically insignificant for firms issuing publicly or privately placed bonds with low covenant intensity or bonds with no additional debt covenants attached.

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1 Introduction

A private placement bond (hereafter PPB)[29] is a corporate bond sold directly to large, mostly institutional investors (Fenn, 2000), not involving any public offering,[30] and with concentrated ownership in a few investors (Houston & James, 1996). In times of decreasing importance of public capital markets, paired with fewer company listings (Gaoet al., 2013), PPBs have become more important, especially in the aftermath of the Global Financial Crisis (GFC).[31] It appears that structural changes in the credit markets have brought private bonds into the capital markets arena. They follow the expansion of the market for collateralized debt obligations of the 2004 to 2007 period, which was fuelled by the interest of institutional investors and characterized by a decrease in spreads of leveraged buyout (LBO) loans (Shivdasani & Wang, 2011). The increase in the supply of debt by institutional investors and reduced spreads, below that demanded by banks for loans to otherwise identical firms (Ivashina & Sun, 2011), appears to make the issuance of PPBs appealing to issuers. However, it is yet unclear whether the use of PPBs impacts firm value ex ante and if so, whether it increases or decreases firm value. Event-study driven research has

[29] Throughout this paper I will use the terminology "private placements bonds", "private placements", and "private bonds" interchangeably, and likewise for "public placement bonds", "public placements" and "public bonds".

[30] An alternative, more formal definition would refer to the exemption of section 4(2) of the Securities Act of 1933, which exempts from registration transactions not involving any public offering. Primary offerings using this exemption are often referred to as private placements. However, since European companies are not subject to US legislation, there are primary offerings without exemption from registration in their home country that are nevertheless private placements.

[31] Debt funding is the primary source of external funds for firms after their establishment, for which they are equity financed. It accounts for approximately 95% of total new external finance (Whited, 1992). Private debt from non-bank funding sources has gained in importance (Kraemer-Eis et al., 2014) in the aftermath of the Global Financial Crisis. The market share of PPB issues within primary market bond issues in the Euro Area (EA), one important source of non-bank funding, has more than doubled. It has grown from approximately 14% in 2008 to 30% in 2015 (Böni & Rietmann, 2016), yet little is known about the valuation effect of issuing PPBs. Together with PUBs, PPBs appear to substitute bank loans (Kraemer-Eis et al., 2014), especially in times of tight bank lending and poor bank performance across European banks (Becker & Ivashina, 2014). Public debt markets appear to not fully mitigate the effects of bank distress, especially during financial crisis (Carvalho et al., 2016). It is expected that market-based funding is continuing it's growth (Cour-Thimann & Winkler, 2013), for example through the issuance of PPBs.

resulted in a consensus that bank loans are unique relative to other financial contracts, with announcements of them resulting in positive abnormal returns. In contrast, announcing public bonds appear to generate no significant abnormal returns and those of stock issues yield negative abnormal returns. Given the concentrated ownership of PPBs in a few institutional investors, it is therefore an empirical question whether PPBs resemble more bank loans or public bonds and whether they create positive or negative stock price reactions when announced.

Prior literature (Mikkelson & Partch, 1986; James, 1987; Harvey et al., 2004)[32] is ambiguous and provides inconclusive evidence related to the stock price reactions to the announcement of private debt. These studies generally adhere to the asymmetric information approach presented in Myers & Majluf (1984) and posit that bank debt, for example, can be seen as a form of inside debt (Fama, 1985), providing information about the value of the firm's growth prospects (James, 1987). Stock price reactions are rationalized based on moral hazard models provided by classical agency theory. It is proposed that shareholders of levered firms may have incentives to engage in actions that are damaging to debtholders. They may engage in risky projects, asset substitution or forgo positive net present value projects leading to underinvestment (Galai & Masulis, 1976; Jensen & Meckling, 1976; Myers, 1977). Covenants are found to be effective instruments in mitigating such agency problems in bond contract design (Smith & Warner, 1979) and provide important ex ante instruments in optimal financial contracting. Since these restrictions imposed by the use of covenants are costly to the firm, they must confer some offsetting benefit (Smith & Warner, 1979). The benefit of using covenants is the reduction in agency costs, which translates into a lower cost of debt. Consistent with this prediction, Bradley & Roberts (2015) find that the inclusion of covenants in loan agreements reduces the cost of debt. Reisel (2014) likewise finds that covenants reduce the cost of debt for public bonds. However, she also finds that covenants restricting a firm's financing lead to a

[32] Mikkelson and Partch (1986) and James (1987) find a positive stock response to the announcement of bank loans but no abnormal returns to the announcement of private placements of debt (Mikkelson & Partch, 1986) or marginally negative abnormal returns to the issuance of private placement bonds to insurance companies (James, 1987). Harvey et al. (2004) find an average abnormal return to privately placed domestic bond issues of -1.04%, however, only marginally significant.

marginally significant increase in the cost of debt. This indicates that the effect of covenants may under certain circumstances be increasing the cost of debt. For example, Böni et al. (2019) find that financing covenants are used to facilitate debt renegotiation, resulting in higher ex ante spreads as investors request a compensation for contracting under higher uncertainty. Leaning on incomplete contracting theory, they suggest that firms may prefer private debt markets as they seek the benefits of flexible debt renegotiation at the expense of financing limitations.

This study controls for the ex ante effects of using covenants in PPBs as compared to public bonds. Prior studies find the announcement of covenant violations negatively affects stock prices (Beneish & Press, 1995; Chava & Roberts, 2008 and more recently Nini et al., 2012)[33]. Also, Core and Schrand (1999) have shown that covenants convey information to investors when earnings announcements are made. According to them, the stock market reaction is related to the informativeness of earnings announcements with respect to potential covenant violations. Covenants mitigate the effects of agency and information problems based on implicit limitations. As shareholders value compliance with monitored covenants (Harvey et al. 2004), covenant use may therefore also convey information ex ante. To the best of my knowledge, no empirical study has yet directly addressed this question. The issuance of PPBs provides an interesting setting to examine it. I empirically test whether the use of covenants affects firm valuation ex ante, that is at the announcement of the issuance of PPBs. Moreover, this study examines whether higher covenant intensity increases or decreases ex ante stock price effect and how these effects can be explained.

This paper examines 325 corporate bond issues by 147 firms and includes 188 public placement and 137 private placement bond issues in the years 2002 through 2015. It provides direct evidence that, on average, restrictive covenants in private debt contracts affect shareholder value *ex ante*. I find that issuing PPBs with below average covenant intensity results

[33] According to Beneish and Press (1995) announcements of technical default are associated with significant stock price declines. Higher costs of borrowing as a consequence of new restrictions on firms' opportunities following the renegotiation of contracts impose wealth losses of 1.4% on shareholders. Declining investments following a covenant violation are evidenced by Chava and Roberts (2008) or Nini et al. (2012).

in statistically insignificant abnormal returns. In contrast, average covenant intensity results in negative and statistically and economically significant abnormal returns. The data suggests that the negative abnormal returns increase in covenant intensity and are affected by financing covenants. Also, it is evidenced that the issuance of PPBs is valued differently by the stock market than that of issuing publicly bonds (PUBs), for which no significant abnormal returns are detected. I hypothesize and show that these abnormal returns are related to uncertainty about the credit risk of an issuer. To make this study comparable to previous work, I calculate and present the cross-sectional t-test as proposed by Brown and Warner (1980) together with the standardized residual test developed by Patell (1976). Additionally, to account for potential event day clustering, the parametric standardized cross-sectional test of Boehmer et al. (1991) and the nonparametric test proposed by Kolari and Pynnonen (2011) are employed. Moreover, to account for potential event day clustering in an alternative way, I drop PPB issues with overlapping calendar day announcement dates and find that abnormal returns are not affected. Additionally, a comprehensive set of confounding events such as earnings, dividends, merger and other financing announcements as well as analyst recommendations in the event window is evaluated. Given that negative abnormal stock market reactions persist when there are no confounding events and when there are confounding events, I conclude that these events do not invalidate the findings.

Using the market model[34] to estimate normal returns, this study provides evidence for a mean (median) cumulative average abnormal return (CAAR) for an event window -10;+30 in the magnitude of –5.3% (-4.3%) for firms issuing PPBs with average covenant intensity and -6.8% (-7.4%) for firms issuing PPBs with financing covenants attached. The CAAR turns more negative by -1.5% (-3.1%) when financing covenants are attached to PPBs. Abnormal returns for firms issuing PPBs with such restrictions appear to convey more negative information than those with high covenant intensity but no financing restrictions. This result contrasts the CAAR for firms issuing

[34] The CAAR is also calculated using the constant mean return model. The results are of comparable magnitude and shall be reported later in this paper.

PUBs, which is between –0.19% and –0.28% and statistically not different from zero. To put this number in perspective, for the average market capitalization of firms issuing PPBs of € 11.7 billion, the mean CAAR represents approximately € 620 million to € 795 million in abnormal firm value reduction. Compared to the average issue amount of € 1.6 billion, the valuation effect of issuing PPBs appears to be substantial. On average, 44% of the funds raised in the form of debt are lost in firm value.

Other than with public bonds (PUBs), the detailed bond indentures for PPBs are only communicated to the market a few days after the bond announcement date and the CAAR turns statistically significant only after this information has reached the market. This finding provides further evidence that not the type of security, here a PPB, drives abnormal returns, but that these returns are primarily related to the use of restrictive covenants and especially financing covenants. In line with this, I find that the CAAR for firms issuing bonds with few restrictive covenants or no financing covenants attached are not different from zero.

Moreover, in line with the costly contracting hypothesis of Smith and Warner (1979), I find an inverted U-shape[35] for the relationship between the CAAR and covenant intensity for firms issuing PPBs, allowing to contrast empirically the benefits of including restrictive covenants with the cost of doing so. The CAAR starts to decrease (becomes negative) at an average of approximately 7 covenants attached to a PPB. The cost to shareholders of limiting managerial discretion appears to outweight the benefits after this level. 66% (52%) of firms issuing PPBs (PUBs) overshoot this level of covenants attached to a bond. Additionally, 42% (18%) of firms issuing PPBs (PUBs) accept financing covenants. The 24 percentage-point difference in the mean number of firms accepting financing covenants is highly statistically significant at the 1% level.

I test a set of alternative explanations for abnormal returns using OLS regressions. A placement dummy variable indicating if a bond placement is private is negative and highly statistically significant in all specifications. Interacting it with covenant intensity, it is insignificant

[35] The inverted U-shape is tested following the test proposed by Lind and Mehlum (2010) and additional guidance provided by Haans et al. (2016).

for PUBs but significant for PPBs, confirming the use of covenants affects firm value ex ante and if PPBs are issued. All else equal, having the right to retire a bond prior to its maturity renders the CAAR less negative by 4.4%. The data suggests that firms having the option to free themselves from the embrace of covenant restrictions experience less negative returns. Next, I find a positive coefficient for the 144A registration variable[36], significant at the 10% level. It appears that, ceteris paribus, issuing registered PPBs results in a CAAR less negative by 4.7%, on average. In line with prior research (Fenn, 2000; Arena, 2011; Chaplinsky & Ramchand, 2004) I conclude that a distinction between 144A-registered bonds and unregistered bonds must be made. Equity market volatility (VIX) is positively related to abnormal returns, significant at the 5% level. The MSCI index return over a 180 days period (MSCI) is negatively related to abnormal returns, significant at the 10% level. A one standard deviation increase in VIX reduces the CAAR by 5%, whilst a +/- 5% return on the index creates a -/+ 0.7% change in the CAAR. A set of robustness tests, such as the assessment of potential inferences from event date clustering or the testing of a comprehensive set of confounding events do not change the findings in any material way.

I hypothesize uncertainty about credit risk, and especially bankruptcy risk, may explain the relatively large abnormal returns. I use two proxies to test this hypothesis. First, as in Morgan (2002) or Akins (2018), I employ the pattern of disagreement between credit rating agencies (CRAs) and include this factor in the OLS regression specifications. Second, Altman’s (1977) Z-score is likewise used as an indicator for an issuer’s bankruptcy risk. The two tests do not change the results in material ways but provide further evidence that covenants are priced in private but not in public bonds.

[36] The Securities Act provides that no securities may be offered or sold in the US unless the securities are registered with the SEC or an exemption from registration is available. Registration with the SEC is an expensive and time-consuming process and many international securities issues are structured to qualify for an exemptions from SEC registration. A commonly used exemption is Rule 144A., It allows companies to market debt directly to private institutional investors rather than going through a more time-consuming public securities issuance process. Rule 144A was adopted in April 1990 and established conditions under which private placements can be traded among qualified institutional buyers'. As Fenn (2000, p. 385) shows, firms use Rule 144A to facilitate speedy issuance of public-like securities, not to issue securities that are structurally different from public securities”.

This paper contributes to the literature in various dimensions: First, while previous research has shown that the presence of covenants is motivated and rationalized by their ability to mitigate agency problems (Jensen & Meckling, 1976; Smith & Warner, 1979; Tirole, 2006) and that covenant violations impact firm investment activities *ex post* (Beneish & Press, 1995; Chava & Roberts, 2008 and more recently Nini et al., 2012)), it has been less clear whether the inclusion of restrictive covenants impacts firm value *ex ante*. This paper adds to the literature on the choice between private and public debt and provides direct empirical evidence for a relationship between covenants and firm valuation *ex ante*. Covenant provisions announced to the market in the process of issuing PPBs appear to transmit new information. If stock price effects were solely driven by the type of security sold to investors (Mikkelson and Partch, 1986), then abnormal returns should be observed immediately upon the announcement of a private placement and cease to be observed after a short event window. However, I find evidence that the negative CAAR for firms issuing PPBs is only detected for longer event windows, that is after the full disclosure of the covenants attached to a bond and communicated in the bond indentures. For PPBs, these indentures are released to the market only a few days after a successful bond placement. Second, it provides evidence that firms accepting sub-optimal restrictions of future debt issuance (Smith & Warner, 1979) might be subject to increased bankruptcy risk. It appears that the marginal benefit of covenant intensity to shareholders decreases with increasing covenant intensity and turns negative from a tipping point. Mitigating classical agency costs up to a certain level (Jensen & Meckling, 1976; Smith & Warner, 1979), beyond that tipping point, the use of covenants appears to be related to managing bankruptcy costs and flexible debt renegotiation. Third, this paper contributes to the literature that suggests that bond covenants, unlike loan covenants, are written loosely[37] and that raises concerns about the effectiveness of

[37] A recent example of such loosely written covenants in public bonds and related investor push against bond rules used by Walmart. As described in the Financial Times (FT, 2018), the retailer used legal language as part of a large $ 16 billion debt fundraising related to an acquisiton. It would allow Walmart to execute a make-whole-call and buy back a $ 8.5 billion portion of the debt at a value below an agreed 101% of face value if it does not complete the planned acquisition. This buy back option created some investor push back since it is standard practice to pay investors for deal delays. Investors requested Walmart to rewrite these bond rules.

bond covenants in mitigating agency problems (Beneish & Press, 1995; Chen & Wei, 1993; Nini et al., 2009). While this strand of literature suggests that bond issuers put little effort into financial contracting in terms of mitigating agency problems, I find that the inclusion of covenants significantly and importantly affects the stock price of firms issuing private bonds. If this is the case, it appears to be unreasonable to assume that bond covenants on PPBs are written loosely. This finding is in line with Reisel's (2014) observations with regard to public bonds.

The rest of the paper is organized as follows. The next Section provides a review of related literature. Section 3 contains a description of the data and methodology and presents descriptive statistics. In Section 4, I estimate the magnitude of the wealth effects of issuing PPBs to stockholders and present the empirical results. In Section 5, a set of potential other explanations for the observed wealth effects are explored. Section 6 contains robustness tests such as for example the assessement of potential inferences from event date clustering, the testing of a comprehensive set of confounding events. In Section 7 I test whether uncertainty about credit risk explains abnormal returns. A brief conclusion is provided in Section 8.

2 Related Literature

2.1 Capital Structure Theory, Agency Theory and the Use of Covenants

Capital Structure Theory. Different theories related to the capital structure choice exist. Following Barclay and Smith (2005), they can be grouped into three broad categories: (1) taxes, (2) contracting costs and (3) information costs.

First, the extent to which a company profits from interest tax shields may have an impact on firm value. The value of a debt financed company equals that of a fully equity financed firm plus the present value if its interest tax shields from debt financing. Adding debt to the balance sheet creates a tax advantage in the magnitude of the company's marginal tax rate, multiplied by the interest paid to debt providers. Increasing leverage, rather than increasing equity, thus increases the value of the firm since tax can be deducted from interest payments but not dividends. However, these tax benefits must be compared to higher contracting costs.

Second, contracting costs describe the costs of financial distress and bankruptcy costs. The optimal debt structure is when marginal bankruptcy costs associated with debt are equated with marginal tax benefits. This trade-off is described in trade-off theory in Leland (1994).

Third, information costs are related to the fact that often managers have better information about the value of the firm than outside investors. The problem of asymmetric information has led to three distinct theories of financing decisions: (a) market timing, (b) signaling and (c) the pecking order. Market timing is related to issuing overpriced securities and to avoid issuing underpriced ones. Many studies have shown that investors mark down the share prices within seasoned equity offerings given the fact that they understand management's incentives to time the markets. These studies are summarized in the next Section. Signaling theory, like market timing, is based on the assumption that management disposes of insider information. Here, financing decisions are designed primarily to communicate confidence of the management regarding the prospects of the firm. As has been described in Ross (1977), adding more debt can serve as a signal of higher expected future cash flows.[38] Finally, the pecking order theory presented by Myers and Majluf (1984) proclaims that management seeks for the cheapest available source of funds and therefore prefer internal financing (retained earnings) to external funds. If external funds, then debt is preferred to equity because of the lower information costs associated with debt. Issuing equity is seen as the last resort of financing and only used when debt capacity has been exhausted.

Agency Theory. With agency relationships as described in Jensen and Meckling (1976) or Smith and Warner (1979), the information asymmetries between managers and investors may lead to situations in which managers will not always act in the best interest of the principal. As Billett et al. (2007, p. 697) put it: "One of the most important costs of debt financing is the potential for conflicts between stockholders and bondholders over the investment and financing

[38] In the context of debt choice, it is assumed that firms with proprietary information that is likely to be valuable to competitors will prefer private over public debt as private lenders have the ability to keep sensitive information confidential (Campbell, 1979). Proprietary information may, for example, consist of R&D informational advantages over competitors (Bhattacharya & Ritter, 1983). Krishnaswami et al. (1999) show that firms with higher unexpected earnings rely more on private debt than other firms.

policies of the firm." Several debtholder-shareholder agency conflicts must be considered in this context, namely conflicts over dividends, claim dilution, asset substitution and underinvestment. The asset substitution problem according to Jensen and Meckling (1976) arises from the incentive of shareholders to substitute existing assets with riskier assets because they have unbounded upside potential and limited liability. Galai and Masulis (1976) explain the motivation for asset substitution by modelling the equity of a levered firm as a call option on the firm's assets. Shareholders have an incentive to increase the volatility of firm assets to increase the value of their call option. The underinvestment problem is explained in Myers (1977): Levered firms' shareholders receive cash flows that remain after paying off debt. This incentivizes them to accept only projects with a net present value (NPV) exceeding the face value of debt. As a result, managers forego some positive NPV projects. Too much debt can lead to underinvestment. However, as is described by Jensen (1986), too little debt can lead to overinvestment. Here, managers of mature firms with few profitable projects use excess cash to sustain growth by overinvesting in their core business or diversification into unfamiliar businesses, for example through acquisitions.[39]

Covenants. The costly contracting hypothesis offered by Smith and Warner (1979) is that efficient control of stockholder bondholder conflicts can increase the value of the firm and that (p.121) "there is a unique optimal set of financial contracts which maximizes the value of the firm." Covenants are written into debt contracts to control agency problems (Berlin and Mester, 1992). The main concerns may arise from information asymmetries leading to asset substitution where shareholders invest in risky projects given bounded (limited) liability but unlimited benefits (Jensen & Meckling, 1976; Galai and Masulis, 1976). Myers (1977) shows that moral hazard may lead to underinvestment problems as firms with risky debt forgo positive net present value projects when cash flows primarily flow towards debt repayments. Rational investors, in this moral hazard argumentation, will ask higher returns or intensify monitoring of such borrowers.

[39] For a more in-depth review of overinvestment problems such as for example empire building and empire preservation see Stein (2003).

Extending the moral hazard view, in their incomplete contracts approach, Aghion and Bolton (1992) find that (p. 490) “not all potential conflicts of interest between the entrepreneur and the investor can be resolved through ex ante contracting”. According to them, rather than ex ante contracting, a state contingent (re-)allocation of control rights over assets ex ante minimizes agency problems. Based on incomplete contracting theory, Rajan and Winton (1995) propose to design contracts that strengthen the monitoring incentives and suggest this is done by exercising control rights contingent on the monitoring outcome. According to them, incentives to monitor are improved by relying on covenants written on verifiable information.[40] Rajan and Winton (1995) predict that higher risk and high information asymmetries are associated with greater control allocations and incentives to monitor. Covenants assign control to creditors by giving them strong decision rights providing protection against information asymmetry (Garleanu & Zwiebel, 2009). Lenders receive an option to renegotiate loan terms by threatening default following a decline in economic performance (Aghion & Bolton, 1992; Dewatripont & Tirole, 1994; Garleanu & Zwiebel, 2009) or accelerate debt contracts (Roberts & Sufi, 2009; Denis & Wang, 2014; Prilmeier, 2017). Recent research has shed more light on the use of covenants. Focusing on debt renegotiation, Demerjian (2017) examines the use of financial covenants when contracting for debt under uncertainty. He finds that a lack of information about future economic events and their consequences for the borrower’s creditworthiness are positively related to covenant intensity. Nikolaev (2017) studies whether the demand for monitoring explains the score for renegotiation in private debt contracts. He finds that monitoring mechanisms, such as the use of covenants, are positively related to renegotiation intensity.

[40] Early accounting literature has contributed to this topic. For example, Leftwich (1983, p.27) noted: “Just as it is in the interest of stockholders to negotiate restrictions on a firm’s financing and investment decisions, it is also in their interest to negotiate accounting measurement rules that reduce management’s ability to circumvent the restrictions by a judicious choice of accounting methods.” According to (Watts, 2003), to cite an important contributor in the field of accounting conservatism, high financial reporting quality reduces borrower opacity and, under the agency perspective, the agency cost of debt. In a more recent study, Christensen et al. (2016) discuss how the use of accounting information in contracts enhances contracting efficiency. They provide a comprehensive literature review with regards to accounting conservatism. I do not include this stream of large accounting literature since the level of analysis is focussed towards the existence of restrictions on financing and investment decisions, rather than the quality of accounting information related to those restrictions.

2.2 Evidence on Private Placement Bonds and Covenants

Private Placement Bonds. Prior research on PPBs consists of studies focusing on the determinants of debt choice (Krishnaswami et al., 1999; Cantillo & Wright, 2000; Denis and Mihov, 2003; and Arena, 2011) and on the pricing differences between PPB and PUB (Blackwell & Kidwell, 1988; Chaplinsky & Ramchand, 2004; Fenn, 2000; Kwan & Carleton, 2010). There is agreement that firms issuing private debt are of lesser credit quality than their public counterparts (Blackwell & Kidwell, 1998; Cantillo & Wright, 2000; Denis & Mihov, 2003; Kwan & Carleton, 2010). Denis and Mihov (2013), for example, find that the median private borrower is smaller, has fewer tangible assets, and has lower credit quality than the median public borrower. Thus, default risk may be an obvious explanation for the differences in abnormal returns related to the issuance of PPBs. However, as Mikkelson and Partch (1985) and James (1987) evidence, announcement effects are, in general, not explained by differences in default risk.

Another observation in prior studies is that more information asymmetries and agency costs must be expected in firms issuing PPBs (Krishnaswami et al., 1999; Cantillo & Wright, 2000). Krishnaswami et al. (1999) show that flotation costs and agency costs drive a firm's debt choice and that firms that rely more on private debt operate under greater information asymmetry. Consequently, debt covenants are expected to be more restrictive in private placements than in public placements (Smith & Warner, 1979) and with increased information asymmetry. This is empirically evidenced by Rajan and Winton (1995), Chava and Roberts (2008), Demiroglu and James (2010), Skinner (2011), Christensen and Nikolaev (2012) and Hollander and Verriest (2016). Also, as shown by El-Gazzar and Pastena (1990), Kwan and Carleton (2010) and Bradley and Roberts (2015), private debt contains more covenants than does public debt.

Covenants. More recent studies provide evidence that covenants reduce the cost of borrowing. Examining a large dataset of 4267 public bond issues, Reisel (2014) finds that such cost reductions can be as high as 75 basis points. Using a large database of private loans, Bradley and Roberts (2015) find a negative relation between yields on corporate debt and the presence of covenants. The presence of covenants reduces the cost of borrowing. Böni et al. (2019) find that the inclusion of restrictive covenants in private bonds explains much of the excess spread of private bonds over public bonds and that the relationship between spread and covenant intensity is described by a convex pattern. They find that considering this optimum a firm can reduce the cost of debt by an economically significant 96 basis points. On the other hand, they evidence that the cost reduction decreases with increasing covenant intensity and suggest that the costs of using restrictive covenants may exceed the benefits after an optimum.

Other previous studies identify a link between covenants and firm value (Beneish & Press, 1995; Core & Schrand, 1999, Harvey et al., 2004; Kahan & Tuckman, 1993;). Beneish and Press (1995) analyze 87 announcements of technical defaults[41] in lending agreements and show that they are associated with significant stock price declines, imposing wealth losses of 1.4% on stockholders. In this vein, Core and Schrand investigate the effect of earnings announcements of 233 financial institutions. They find that covenants convey information to investors when earnings announcements are made. According to them, the stock market reaction is related to the informativeness of earnings announcements with respect to potential covenant violations and greatest for firms near violation. Kahan and Tuckman (1993) document the wealth effects of covenant modifications related to 42 bonds of 29 listed firms going through the process of consent solicitation and find positive abnormal returns in the amount of 9.5%. Harvey et al. (2004) investigate announcement returns of syndicated bank debt, public bonds and private placement of bonds. Whilst their study is focussed on syndicated bank debt, for which they look at 658 term-loans and 185 credit agreements, they also analyze the announcement returns for 121 international privately placed bonds and 95 privately placed domestic bonds. They find an abnormal return for the domestic private bonds of – 1.04%, significant at the 10% level. According to them, bond issues of firms with high agency problems, measured by above-median percent tangible assets, as opposed to bond issues of firms with less agency problems, measured by below-median percent tangible assets, result in negative / positive abnormal returns in the

[41] They define technical default as the violation of accounting-based covenants in lending agreements and do not regard firms that default on debt service as technical defaulters.

amount of – 0.43% / 0.27%. Whilst they take a firm's assets in place and future growth options into account, Harvey et al. (2004) do not assess the impact of covenants on announcement returns.

2.3 Evidence on Abnormal Returns related to Security Issues: What we know from Event Studies

Event studies dominate the empirical research in the area of corporate finance (MacKinlay, 1997). The short-horizon event study is considered a workhorse of corporate finance (Harrington & Shrider, 2007) and dates back to the seminal work of Fama et al. (1969), who examines the process by which stock prices adjust to the information that is implicit in a stock split, and other early studies discussed (for example, Manne, 1965) and assessed the price effects of mergers (Eckbo, 1983).[42]

Event studies related to the financing of firms followed.[43] These studies generally find that offerings of common stock (SEOs) result in negative abnormal returns (Mikkelson & Partch, 1986; Asquith & Mullins, 1986; Masulis & Korwar, 1986; Carlson et al., 2006; Lyandres et al. , 2008 or Johnson et al., 2018), whilst the announcement of the public issuance of straight debt appears to result in average abnormal returns close to zero (Eckbo, 1986; Mikkelson and Partch, 1986 or James, 1987).[44]

Both, Mikkelson and Partch (1986) and James (1987), evidence a positive and statistically significant response to the announcement of bank loans in the amount of + 0.9% and + 1.93%, respectively.

In explaining the difference in announcement effects between SEOs, straight debt issues and bank loans, these studies generally adhere to the asymmetric information approach

[42] For a survey of this early work related to mergers, see Jensen and Ruback (1983) or Jarrell et al. (1988).

[43] For a comprehensive review of event studies of financing decisions, see Smith (1986).

[44] Smith (1986) provides additional empirical evidence for this.

presented in Myers & Majluf (1984). Managers, according to their approach, profit from an information advantage compared to outsiders regarding the prospects of a firm's business or regarding the correct pricing of firm assets. Managers have an incentive to issue equity when they think shares are overpriced and investors, perceiving this conflict of interest, revalue the stock at a new and lower price. Referred to as the "pecking order" theory of financing, managers rely on internal sources of funds and prefer debt over equity financing to finance new investments. Information asymmetries between managers and investors are also used to explain positive announcement effects of bank loan issues. Fama (1985) has argued that bank debt can be seen as a form of inside debt. Banks are considered to have inside information about the value of the firm's growth prospects (James, 1987) and act as delegated monitors (Gorton & Winton, 2003) with high incentives to monitor (R. Rajan & Winton, 1995). Thus, banks have information about the borrower that public security holders don't, avoiding some important agency problems.

Whilst the announcement effects of SEOs, straight debt and bank debt are well researched and explained, only very few studies include private placements of debt into their study design. Additionally, the results of these few studies are mixed. Mikkelson and Partch (1986), for example, find no statistically significant abnormal returns for 80 private placements of debt and do not offer a discussion related to this finding. They focus more on public offerings and do not explore differences in the stock price response associated with PUBs and PPBs. In contrast, James (1987) shows marginally statistically significant negative announcement effects in the amount of – 0.91% for 37 private debt securities placed with insurance companies. This finding contrasts his argument that private placements are similar to bank loans given the information advantage of private buyers over public security buyers. The inside debt argument as presented by Fama (1985) and used in James (1987) to explain positive stock price reactions associated with bank loans suggests that announcements of PPBs should result in a non-negative stock price response. However, prior studies either find no statistically significant or negative abnormal returns. Various researchers replicate James' (1987) paper and confirm his findings, often with qualification. For example, they show positive stock price reactions for lenders with high reputation (Billett et al., 1995) or syndicates with few lenders (Preece & Mullineaux, 1996).

As Leary and Roberts (2010) propose, the pecking order hypothesis of Myers and Majluf (1984) may not accurately describe financing decisions.[45] Whilst it is based on information asymmetries between managers and investors and posits that a preference ranking over financing sources exists, it appears not to explain the negative announcement returns of PPBs that I find. Private placements have many of the same features as bank loan agreements (James, 1987) and one would expect increased monitoring and positive, rather than negative, announcement returns for firms issuing PPBs. Also, evidence from private equity placements (Wruck, 1989, Hertzel et al., 2002) and convertible debt private placements (Fields & Mais, 1991) contrast with the pecking order hypothesis. In contrast to public equity placements (SEOs), empirical research related to the announcement of private equity placements shows significant positive returns for firms issuing it. Wruck (1989), for example, finds statistically significant abnormal returns of 4.4% for firms issuing equity privately. He attributes the positive announcement effect to a better alignment of interest and value-enhancing monitoring following an ownership concentration related to private equity issues. Hertzel and Smith (1993) argue that anticipated monitoring benefits from private sales of equity causes the positive abnormal returns. Hertzel et al. (2002) find a positive announcement period return of 2.4% associated with private equity issues. Given that they find long-term negative returns for the issuing firms, they conclude that investors might be overoptimistic about the prospects of firms issuing private equity.

It appears that the nature of a security issue (public vs. private) may contain different information. As with private equity, private placements of convertible debt appear to result in abnormal returns different from public placements. For example, Fields and Mais (1991) find significant positive average abnormal returns of 1.8% to announcements of 61 private placements of convertible debt. They conclude that privately placed convertible debt issues convey

[45] Also, they provide an interesting summary of studies scrutinizing the predictions of the pecking order hypothesis in their paper introduction (p. 332).

favourable information about the firm. Their results contrast those of Dann and Mikkelson (1984), who find negative abnormal returns for firms issuing publicly placed convertible debt. Whilst both studies on the issuance of convertible debt provide evidence that such issues convey (un)favourable information about the issuing firms, the specific nature of such information remains unidentified.

I rationalize abnormal returns related to the issuance of PPBs based on agency costs of debt as discussed in Jensen and Meckling (1976) and Myers (1977) and the costly contracting hypothesis offered in Smith and Warner (1979). It is suggested that abnormal returns associated with the announcement of PPBs are related to the way agency problems between bondholders and shareholders are mitigated, i.e. by the use of restrictive covenants.

3 Data and Methodology

3.1 Data

I collect data from S&P Capital IQ (henceforth S&P) and Bloomberg and consider private and public bond issues. The choice of time period is driven by the fact that S&P's coverage of rating scores[46] only starts from January 2002. It ends in 2015. The sample observation period starts in 2002 following the dot-com bubble and includes the Global Financial Crisis in 2008, followed by the European Debt Crisis. This long observation period, which includes complete business cycles as well as significant shocks, "can enhance the robustness of the results of the empirical investigations" (Chen et al., 2011, p. 980). Debt issues of the years 2002 to 2015 are selected by geographic location, offering date, industry classification, security type and security

[46] S&P rating scores are not identical to S&P ratings, which would be available before January 2002. The rating score is described in more detail below and in Appendix B.

features[47] from S&P. I select issuers domiciled in Europe under the condition that their ultimate parent company is domiciled in Europe. This selection reveals 11,037 public and 1,340 private debt issues. Following Chen et al. (2011), Denis & Mihov (2003) and Eom et al. (2004), financial firms are eliminated from the sample because they are regulated and because of their balance sheet structures being systematically different from non-financial companies.[48,49] Furthermore, of all private debt issues only 40 issues have been issued in currencies other than US Dollars (USD). Following Beber et al. (2009), who analyze liquidity and quality effects on European bond spreads in their research and who eliminate bond issues with sparse data, all bond issues in currencies other than USD are eliminated.[50] As in Chen et al., (2011) or Lin et al. (2011), debt issues must have a maturity greater than one year to be considered in the sample. Ten public short-term debt issues are therefore eliminated from the sample. Bonds with maturities exceeding 30 years are

[47] Cut-off-date for the issue information is September 5, 2016. The geographic selection excludes issues of companies headquartered in locations other than Europe (Africa / Middle East, Asia / Pacific, Latin America and Caribbean, USA and Canada). Corporate debentures and offering dates starting January 1, 2002 and ending December 31, 2015 are considered. Other security types (such as for example agency debenture, asset backed securities, bridge loans, convertible bonds, government bonds, LCs etc.) are not considered in the selection and therefore excluded. Security features "public placement" and "private placement" (including traditional private placements and Regulation 144A private placements) are selected.

[48] The Global Industry Classification Standard (GICS) is used to select and eliminate firms from the financial services industry from the sample. The primary industry code "finance" is applied. Furthermore, visual inspection of the data and the application of keywords is used to control for a correct elimination of firms from the financial services industry. Firms with missing industry classification are verified using www.moodys.com and www.bloomberg.com as primary sources for this additional check. For some issues, company specific internet pages were used.

[49] According to Carey et al. (1998) the aggregate equity-to-assets ratio at the end of 1995 was 11.1% for finance companies and 8.3% for commercial banks. As confirmed by the Basel III introduction and the debate on Basel IV, the leverage in the banking industry with a minimum tier 1 capital ratio (core equity capital value compared to the total of risk-weighted assets) of 4% is significantly higher than that of corporates. Also the introduction of a leverage ratio of 33,3 times tier 1 capital, planned for 2018, demonstrates that banks are not comparable to corporates.

[50] Consequently, public debt issues with currencies other than USD are eliminated from the sample. These include EUR (3,193), GPB (645), NOK (576), SEK (451), JPY (159), ARS (1), AUD (30), BGN (1), BRL (1), CAD (7), CNY (9), CZK (33), DKK (20), HKD (21), HRK (2), HUF (10), ISK (13), MXN (1), MYR (2), NZD (5), PEN (1), PLN (54), RON (9), RUB (289), SGD (4), SKK (3), UAH (3), ZAR (1), missing issue currency (30).

likewise eliminated from the sample.[51] Almost all of the eliminations, with the exception of low maturity and currency eliminations, are related to financial firms. From the remaining 1,217 corporate bond issues, 490 are of unlisted issuers and not providing the opportunity to assess any valuation effects. Eliminating these from the sample, results in 727 corporate bond issues of stock listed firms. For some bond issues a package of securities is offered from one issuer at the announcement date. In order to avoid the overweighting of multiple events of the same firm, issues of the same issuer with the same announcement date are consolidated into one portfolio and treated as one event. Issue amounts are aggregated and maturity and covenant intensity are adjusted on a value weighted basis. If in the portfolio one bond has a financing covenant attached then the entire portfolio is considered to have a financing covenant attached.[52] For a security to be included in the sample, it must have no missing return data in the event window and at least 200 daily returns in the entire 270 day observation period. Reduced by bond issues aggregated into a portfolio and those events that do not provide sufficient stock return data, the final sample consists of 325 bond issue events, being 188 public and 137 private bond placements of stock listed firms in the European Area (EA).

3.2 Methodology

I follow the short-horizon event study methodology as described in MacKinlay (1997) and Kothari and Warner (2007). For each security, I use a maximum of 280 daily return observations for the period around the PPB issue announcement, starting at day – 249 and ending at day + 30 relative to the event. Normal returns are estimated using 239 daily returns over event days –249

[51] At the expense of rigour with the benefit of keeping important data in the sample, the upper maturity boundary is set to 30.31 years since this reduces the number of PPB eliminations by 41 issues that have a maturity of in between 30 and 30.31.

[52] This suggestion appears reasonable since private debt issues contain more and tighter covenants in light of relatively lower renegotiation costs (Smith & Warner, 1979, Leftwich, 1983). As is shown in the study of Billett et al. (2007), who investigate 15.504 public debt issues, cross-default provisions are the second most frequent covenants observed (51%) following asset sale clauses (65%) and merger restrictions (also 65%). It can be expected that the frequency of cross-default provisions is higher in private debt contracts.

to –11. I then calculate abnormal returns over the -10;+30 event period together with a series of alternative event periods. The announcement date retrieved from Bloomberg is used to define the event date. According to Bloomberg, the announcement date is the earliest known date a security issue is publicized to the market. To test the costly contracting hypothesis, the market disclosure must include detailed indenture information, especially with regards to covenant intensity. Cumulative average abnormal returns are used to account for potential imprecision in dating the event and uncertainty as to when the full indenture information is available to the market. The use of cumulative rather than daily abnormal returns is justified by a critical assessment of the availability of indenture information on the official announcement date published on Bloomberg: I verify all available company disclosures, such as for example the offering memorandum or the prospectus[53] together with information available on Compustat to evaluate whether complete information is available to the market on the announcement date. Of all private placements, I find conclusive information with regards to full indenture availability for 49 privately and 99 publicly placed bonds. On average, complete information regarding the indentures of a PPB is delayed by 6.3 (mean) to 7 (median) days following the announcement date.[54] In contrast, of the verifiable PUB issues, full indenture information is available to the public approximately one day prior (mean) and exactly at the announcement date (median). The 30 day post event-window is used to reflect and observe the effects from this delayed information availability. Additionally, this design provides estimators for the parameters of the normal return model unbiased by the returns around the event (Campbell et al., 1997). Also, the used event

[53] Typically bond issues sold in the US-market have filings pursuant to Rule 424(b)(3) and other forms (such as for example forms 20-F or 6-K) available.

[54] Disclosure of debt covenants may be required for several reasons (GAAP, stock exchange regulation, SEC regulations etc.). However, bond issuers or intermediaries may choose not to report on covenants in private debt agreements (see Press & Weintrop, 1992, for a related analysis) or do so only with delay, for example within their annual reports. As defined in the market guide of the International Capital Market Association (2016) for European corporate debt private placements, disclosure provisions are typically determined on a case-by-case basis and depending on particular investors' and arranger's requirements and the borrower's situation.

window allows examining whether the market may have acquired information about a security offering prior to the actual event date, since this might be a concern with private placements.

The market model and the constant mean return model[55] are used to examine the valuation effect of private (PPB) and public (PUB) bond offerings and to investigate the nature of information inferred by investors from such offering announcements. The abnormal return of firm i and event date t is the difference of the realized return and the expected return given the absence of an event. The market model assumes a constant and linear relation between individual asset returns and the return of a market index, here the S&P 500 equal weighted index plus the value weighted counterpart as well as the MSCI Europe. For every security, the abnormal return in the event period using the procedure as described in Brown and Warner (1985) is estimated by ordinary least squares (OLS) regressions based on estimation-window observations:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \qquad (1)$$

where $R_{i,t}$ is the observed return for security i at day t and $R_{m,t}$ is the return on the benchmark index (market) for day t, with $E[\varepsilon_{i,t}] = 0$ and $VAR[\varepsilon_{i,t}] = \sigma^2_{\varepsilon i}$.

The constant mean return model is used as the second normal return model. It assumes expected stock returns can differ by company, but are constant over time. The model is:

$$R_{i,t} = \mu_i + \varepsilon_{i,t} \qquad (2)$$

[55] The market model assumes a constant and linear relation between individual asset returns and the return of a market index, here the S&P 500 equal weighted. $A_{i,t}$ is the abnormal return for security i at day t. For every security, the abnormal return in the event period using the procedure as described in Brown and Warner (1985) is estimated: $A_{i,t} = R_{i,t} - R_{m,t}$, where $R_{i,t}$ is the observed return for security i at day t and $R_{m,t}$ is the return on the benchmark index (market) for day t. The constant mean return model assumes expected stock returns can differ by company, but are constant over time. The model is: $A_{i,t} = R_{i,t} - \overline{R}_i$,, where $\overline{R}_i$ is the average of security i's daily returns in the estimation period.

where $R_{i,t}$ is the observed return for security i at day t and μ_i is the average return of security i over the estimation window with $E[\varepsilon_{i,t}] = 0$ and $VAR[\varepsilon_{i,t}] = \sigma^2_{\varepsilon i}$. For both methods, abnormal returns are cumulated across time and for several event windows for every firm issuing PPBs or PUBs, which yields the cumulative abnormal return measure (CAR). The cross-sectional average of this measure is the cumulative average abnormal return (CAAR).

The null hypothesis that the CAAR is equal to zero is tested with a set of tests. The cross-sectional t-test as proposed by Brown and Warner (1980) together with the standardized residual test developed by Patell (1976) are used to make this study comparable to previous research. Additionally, to account for potential event day clustering, the parametric standardized cross-sectional test of Boehmer et al. (1991) and and the nonparametric test by Kolari and Pynnonen (2011), being an adjusted version of the Boehmer et al. test (1991), is employed. The test by Boehmer et al. (1991) corrects for both an increase in volatility during the event window (time-series heteroskedasticity) and cross-sectional heteroskedasticity[56] and appears to be robust with regard to cross-sectional correlation of returns due to event day clustering.[57] Since the evidence generally suggests that stock returns are fat-tailed relative to a normal distribution (Fama, 1976), the nonparametric test of Kolari and Pynnonen (2011), who demonstrate both theoretically and empirically that their statistic is reasonably robust to event day clustering, is used. For brevity, only the tests of Boehmer et al. (1991) and Kolari and Pynnonen (2011) are mentioned in the text. The alternative tests are used to make this study comparable to other research and, if not mentioned, the results of these tests do not deviate in material ways from Boehmer et al. (1991) and Kolari and Pynnonen (2011).

[56] The test is found to be a robust parametric test (Harrington & Shrider, 2007) and can be applied to both the average cumulative abnormal return (CAAR) and the average standardized cumulative abnormal return (SCAAR) (see Campbell et al. 1997; MacKinlay, 1997). The test statistic is given in Section 4.5 of Campbell et al. (1997, p. 169).

[57] Boehmer et al. (1991, p. 268) comment their simulation results and conclude that they “are essentially unaffected by the presence of event-date clustering.”.

I use the S&P 500 equal weighted index throughout the paper to estimate normal returns. However, I also use the S&P 500 value weighted index to run a set of robustness tests.[58] Of the 325 events in the sample of this study, 30 issues are announced on the same day as other issues. Assuming these concurring announcements to occur randomly, this may reduce the number of independent observations. I therefore assess potential inference from event date clustering despite the assumed robustness of the used test statistics of Boehmer et al. (1991) and Kolari and Pynnonen (2011). As will be shown, event date clustering does not materially affect the results and leaves the conclusions unchanged.

Potentially confounding events are examined in a next step. Additionally, other potential explanations for the difference in abnormal returns such as differences in the maturity, borrower default risk, borrower size, and purpose of the borrowing etc. are studied. These results are presented in Section 5.

3.3 Summary Statistics

Table 1 presents descriptive statistics and univariate t-tests together with Wilcoxon's ranksum tests of differences for those variables used.

Panel A compares bond characteristics: Maturity and issue amount are skewed to the right and on average, PPBs have a maturity shorter by 0.65 years and an issue amount which exceeds that of PUBs by almost USD 600 Mio. The difference in maturity between PUBs and PPBs is, however, not statistically different from zero. The data suggests that issuers of PPBs use top tier banks more than those of PUBs to place their securities, i.e. in 54% compared to 37% of all issues. As suggested by theory and prior studies, on average, there are more restrictions on managerial

[58] For the largest fraction of the sample, i.e. approximately 34% (31%) of all privately placed bonds (publicly placed bonds), the issuers' main listing is either on the New York Stock Exchange (NYSE), NASDAQ, the Toronto Stock Exchange (TSE) or with PinkSheets LLC (see Table 3). Also,the S&P500 is highly correlated with its European counterpart, the MSCI Europe, for which the correlation coefficient with the S&P500 equal weighted is 0.7 over the entire observation period. It therefore appears accurate to take the S&P500 equal and value weighted indices as the market benchmark. However, the MSCI Europe index is used as an additional robustness test. The results do not change materially and shall be reported in the footnotes of the following analyses.

discretion for firms issuing PPBs as expressed by the number of covenants attached to a bond. On average, PPBs have 8.5 covenants attached, whereas PUBs are issued with an average of 7.0 covenants attached per bond. A detailed overview of the observed frequencies of the 18 covenants measured in PPBs and PUBs is given in **internet appendix I** but not published for brevity. Also, PPBs have 24% more financing covenants attached than PUBs (41% versus 18%). All differences, with the exception of maturity, are statistically significant at the 1% or the 5% level.

Turning to firm characteristics, as shown in **Panel B**, firms issuing PPBs are comparable in age to those issuing PUBs. Measured by their revenues in million Euros (€) (their size of the balance sheet as measured by total assets in million €), firms issuing PPBs are, on average, 41.5% (45%) smaller than firms issuing PUBs. Firms issuing PPBs (PUBs) do not differ significantly in profitability with mean values of 13% (15%). Their leverage is, however, slightly higher by 3% and amounts to 29% (26%) respectively. Their mean rating score is lower by approximately one notch on average. Firms issuing PPB have a rating score of 9.6[59] and a lower rating equal to between BBB and BBB-, on average. This compares to a score of 8.6 or a rating equal to between BBB and BBB+, on average, for firms issuing PUB. Their equity value is smaller as measured by book value (market cap) and amounts to an average of € 7.3 billion (€ 11.7 billion). This compares to firms issuing PUBs with an average equity book value (market cap) of € 21.8 billion (€ 27.28 billion). To gauge a firm's growth opportunities as in Nash et al. (2003) and Barclay et al. (1995), I also compare the market to book ratio.[60] By this measure, firms issuing PPBs with a ratio of 2.35 appear to have more growth options than those issuing PUBs with a ratio of 1.99. However, the difference of 0.37 in market to book is statistically not significant (t = 1.19, z = 1.15).

Table 2 provides information on bond issues by firm domicile. Panel A contains information on the whole sample, including firms issuing PUBs and PPBs. Panels B and C show the

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[59] Note that the best score is 1 and the worst is 18, hence higher scores equate to lower ratings.

[60] More precisely, I use this ratio as calculated in Nash et al. (2003, p. 209) and equal to the book value of assets minus the book value of equity plus the market value of equity divided by the book value of assets.

frequency and domicile of firms issuing PUBs and PPBs respectively. The sample is skewed towards firms domiciled in the United Kingdom, who issue approximately one third of all bonds in the sample, followed by firms domiciled in France, Ireland, Norway and Luxembourg, which all together account for another 40% of all bonds issued or together with the United Kingdom for approximately 74%. When differentiating between firms issuing PUBs (**Panel B**) as opposed to that of firms issuing PPBs (**Panel C**), it appears that firms domiciled in the United Kingdom use the private placement channel more often than others.[61] These firms represent approximately 39% of all PPBs issued. Together with firms domiciled in France and Luxembourg, the firms domiciled in these three countries account for approximately 70% of all PPB issues.

Table 3, Panel A, provides an overview of the issuer's main stock exchange listings. Issuers in the sample are listed on European stock exchanges for about two thirds and on US stock exchanges for about one third. 22.7% of issuers are listed on the London Stock Exchange (LSE), followed by the New York Stock Exchange (NYSE) with 19.7% and Euronext Paris (ENXTPA) with 17.2% of all issuers in the sample. Together with the Nasdaq Stock Market (Nasdaq) with 6.5% and Oslo Stock Exchange (OB) with 8.3% share, these main exchanges account for approximately 75% of all listings. As depicted in **Panels B and C** of Table 3, these weights do not differ importantly when differentiating between issuers launching PUBs as opposed to PPBs. The exception is the Oslo Stock Exchange (OB) which drops to a relative share of 2.9% when looking at firms issuing PPBs whereas the Nasdaq Stock Market together with Pink OTC Markets Inc.[62] appear to pick up the delta.

Table 4 presents frequency information with regards to the offering year and industry affiliation of the issuer firm. Companies are classified according to their principal business activity and according to the Global Industry Classification Standard (GICS) as used by S & P. Of the 325

[61] The UK is leading across Europe in terms of sourcing deal volume for direct lenders (Deloitte, 2019). London's leading position as a financial centre (see London Stock Exchange, 2019, for a comparison of global financial centres) may explain this leading position.

[62] According to their company information, Pink OTC Markets Inc. provides the leading inter-dealer electronic quotation and trading system in the over-the-counter (OTC) securities market in the US.

placements in the sample, 57.9% are PUBs and 42.1% are PPBs. Turning to the frequencies per year, a trend in the increasing number of PPBs in the aftermath of the Global Financial Crisis (GFC) is visible. Approximately 72% (52%) of all PPBs (PUBs) have been issued after 2009. The relative frequency of bond issues per sector relative to the total number of issues over the entire sample period in percent is indicated in the last row of **Table 4**. Firms from the Energy sector appear to issue more bonds than firms from other sectors, leading to a sample skew towards Energy firms. 19.7% (27.7%) of all PPB issues (PUB issues) are from firms representing this sector. Likewise, firms from the IT sector appear to be underrepresented in this sample, both for the issuance of PPBs and PUBs.

4 Empirical Results

4.1 Announcement returns of firms issuing Private Placement Bonds (PPBs) versus Public Placement Bonds (PUBs)

I start by comparing the average CAR (CAAR) for firms issuing PUBs versus PPBs. The abnormal performance among 325 announcements of PUBs (n = 188) and PPBs (n = 137) appears to differ systematically. The results are shown in **Figure 1** and **Table 5**. Figure 1 depicts the plot of the CAAR from event day -10 to +30. I find a negative stock price response associated with the announcement of private placement bonds. Using the constant mean return model (market model), the CAAR for the event window -10;+30 amounts to – 5.9% (- 5.3%).[63] **Table 5** indicates that the CAAR for firms issuing PPBs increases monotonically from the shorter event windows to

[63] Using the MSCI Europe instead of the S&P500 index returns and the market model, the CAAR for private placement bonds and for the event window -10;+30 amounts to -5.4%. The test statistics for this event window and for Boehmer et al. (1991) and Kolari and Pynnonen (2011) are comparable to those using the S&P500 and amount to -4.18 and -3.94. Also, for the issuance of PUBs, no significant CAAR is observed. The results using the MSCI Europe index are summarized in Appendix D.

the -10;+30 window and remains at a relatively high level thereafter. The test statistics for the event window -10;30 of Boehmer et al. (1991) and Kolari and Pynnonen (2011) using the constant mean return model show highly significant results for firms issuing PPBs with t = - 4.09 and - 3.85. Using the market model and these test statistics, the CAAR remains highly significant with t = - 3.74 and –3.52. Contrary to this and in line with prior research, the announcement of a public bond results in a CAAR for the event window -10;+30 statistically not different from zero and between -0.19% using the constant mean return model and 0.82% using the market model. Also, the CAAR for firms issuing PPBs is statistically different from those issuing PUBs in a two-tailed t-test (t = - 3.41) and in a Wilcoxon ranksum test (t = - 3.31).

The negative CAAR for firms issuing PPBs and for a shorter event window of -10;+1 appears to be in line with the finding of James (1987) and is statistically significant at the 5% level using the constant mean return model and between the 5% and 10% level using the market model.[64] However, it emerges from **Table 5** that the event window should be extended beyond a one or two day period following the announcement. The CAAR for PPBs become larger and statistically more significant when longer event windows are considered. This can be explained by the delayed availability of full indenture information to the market, as mentioned above. As shown in Figure 1, the CAAR appears to consistently turn negative after approximately 7 days. This appears to reflect the fact that full indenture information is, on average, only available after 6.3 days following the announcement date.[65] As can be taken from **Table 5, Panel A**, the level of

[64] James (1987) found negative announcement effects in the amount of – 0.91% for private debt securities placed with insurance companies. He used the market model to obtain estimates of abnormal stock returns around the announcement of financing events and for an event window of -1;0. Using the same event window and the markt model, I receive a CAAR of – 1.3%, comparable to James (1987), this result however statistically not being different from zero.

[65] Abnormal returns (for firms issuing PPBs and controlling for the 49 issues for which conclusive full indenture release data is available) increase monotonically from an average -1.3% at the event day (n=9) to -4.69% for event days 1 and 2 (n=2) to -4.8% for event days 3 and 4 (n=3) to -5.5% for event days 5 and 6 (n=10) to -6.92% for event days 7 and 8 (n=14) and decrease thereafter to -3.1% for event days 9 and 10 (n=3), thereafter approaching zero for event days 11 and beyond (n=8).Conclusive information regarding the full market release of indenture information is only available for 35.8 % or 49 out of 137 PPBs. Given the long sample period and the various legislations in which PPBs were issued, it appears to be challenging to collect additional information regarding the release date of full

significance of the CAAR using Boehmer et al. (1991), for example, jumps from the 5% to the 1% level only once longer event windows between -10;+15 and -10;+30 days following the announcement are considered. Also, as expressed by the t-test and using the market model, the difference between the CAAR of PPBs and PUBs becomes consistently statistically significant only for event window -10:+10 and for longer event windows. Analyzing abnormal returns prior to the event day for the event window -10;0 as given in **Table 5, Panel A**, one may conclude from the test statistics that abnormal returns are not different from zero for this event window. Using the market model, all test statistics with the exception of the generalized sign test of Cowan (1992) do not reach the critical values. The generalized sign test of Cowan (1992), however, indicates that the ratio of positive abnormal returns over the event window deviates systematically from that same ratio over the estimation window (t = - 2.21). The concern that the market may have acquired information about a security offering prior to the actual event date, which might be the case with private placements, can therefore not be rejected completely. No statistically significant CAAR is found for firms issuing PUBs.

If stock price effects are solely driven by the type of security sold to investors (Mikkelson and Partch, 1986), then abnormal returns should be observed immediately upon the announcement of a private placement and cease to be observed after a short event window. As can be seen in Figures 1 through 3, this is not the case with the stock price performance of issuers of PPBs compared to that of issuers of PUBs. The CAAR for firms issuing PPBs increases monotonically from the shorter event windows to the -10;+30 window. Compared to other event studies, a relatively slow speed of stock price adjustment to the PPB announcement is observed. As proposed by Fama (1991, p. 1602) short-horizon tests such as this event study represent the "cleanest evidence we have on efficiency". Low market efficiency could be one potential explanation for such a slow reaction of post-event returns. However, as shown in **Tables 1 and 3**, the PPB announcements are made of relatively large firms listed on important stock exchanges

indenture information. As a consequence, rather than allocating new event dates to approximately 36% of the PPBs sample, it is proposed the longer event window together with the related significance tests are used to control for this potential imprecision in measuring the exact event date for firms issuing PPBs .

such as the London Stock Exchange, New York Stock Exchange, Euronext and NASDAQ, to name the top four. It is therefore unlikely that low market efficiency offers an explanation for the relatively low speed of stock price adjustment. Alternatively, stock price effects might be related to the characteristics of security offerings, rather than solely the type of security. If this is the case and under the assumption of an efficient market, then stock price adjustments may only be expected after the disclosure of such characteristics, hence once the full indenture information has been released to the market. As shown in **Table 1**, PPBs have significantly more covenants attached than PUBs, and details on these covenants are communicated within the indenture information. It is an empirical question as to whether the degree of the inclusion of restrictive covenants in bond contract design impacts abnormal returns. As will be shown in the next two sections, these security characteristics in fact drive abnormal returns.

4.2 Covenant intensity and announcement returns

Differences in covenant intensity and the allocation of control rights may affect a firm's actions or investor rights ex post a bond issue (Aghion & Bolton, 1992). Also, covenant intensity is related to the cost of debt (Reisel, 2014; Bradley & Roberts, 2015) and may therefore impact firm value. I proceed to the analysis of stock price effects of bond issues with different levels of covenant intensity. As described in **Table 1**, covenant intensity for firms issuing PPBs is different from that of firms issuing PUBs. On average, firms issuing PPBs are more restricted than those issuing PUBs. This difference leads to the empirical question whether covenant intensity impacts abnormal returns. Devos et al. (2017, p.2), for example, suggest that "it is the intensity of covenant provisions that matters the most to adjustment speed". According to them, higher intensity lowers the speed of capital structure adjustment. As in Devos et al. (2017) and many other studies[66], I use covenant intensity ("***covscore***") to describe the number of covenants

[66] For example in Billett et al. (2007), Bradley and Roberts (2015), Hollander and Verriest (2016), Demerjian (2017) or Prilmeier (2017).

attached to a bond and gauge the cost of contracting.[67] The score is the sum of eighteen single covenants[68] available on Bloomberg and takes a minimum value of 0 and a maximum value of 18. A detailed description of these 18 covenants is in **Appendix A**. A bond issue is defined to have a high number of covenants attached if it is equal to or exceeds the number of 8, which corresponds to the sample median of 8 and the rounded up sample mean of 7.7 covenants attached to a bond. 50% of firms (94 out of 188) issuing PUBs and a higher 61.3% of firms (84 out of 137) issuing PPBs have high covenant intensity. The results are given in **Figure 2** and **Table 6**. Figure 2 depicts the plot of the CAAR from event day -10 to +30. The negative stock price response associated with the announcement of PPBs is stronger for firms issuing bonds with high covenant intensity. As shown in **Table 6**, using the constant mean return model (market model), the CAAR for firms issuing PPBs is – 6.6% (– 5.4%).[69] As in Section 4.1, announcement returns for firms issuing PPBs

[67] In these studies covenant intensity is used in a comparable way and essentially counts covenants attached to a debt contract. Other studies that also include a measure of covenant intensity through covenant counts or indexing include Demiroglu and James (2010) or Christensen and Nikolaev (2012). Alternatively to covenant intensity, the probability of covenant violation is often considered a proxy for borrower riskiness or the degree of agency conflicts (Demerjian & Owens, 2016). However, measuring the probability of covenant violation includes the measurement of covenant tightness, a concept which exceeds the scope of this study and which is more difficult to measure given the lack of standardization (see Demerjian & Owens, 2016, for a detailed discussion of measurement error challenges in trying to caputre covenant tightness). Additionally, lenders often make adjustments to accounting numbers when defining covenants (Leftwich, 1983) and the numbers reported in Compustat may differ from those defined in a covenant. This implies that tightness is likely to be measured with error. Demerjian (2017) finds no significant differences when conducting robustness tests by exchangeing covenant intensity with a measure of covenant slack or tightness.

[68] A single covenant is coded 1 if it has an entry in the Bloomberg database and 0 if Bloomberg confirms that no covenants are attached to a bond or if Bloomberg entries are missing. I do thus not exclude from my sample bond issues with missing Bloomberg entries but put the number to 0 in order to keep the sample size sufficiently high. Randomly selected issue documents are controlled for the correctness of covenant information, however, and the information is found to be correct. Also, a potential concern over this procedure is addressed in the robustness test section at the end oft he paper and the findings of the paper do not change in a material way if bond issues with no covenant information are exclueded instead of setting the number to zero.

[69] Using the MSCI Europe instead of the S&P500 index returns and the market model, the CAAR for private placement bonds and for the event window -10;+30 amounts to -5.0%. The test statistics for this event window and for Boehmer et al. (1991) and Kolari and Pynnonen (2011) are comparable to those using the S&P500 and amount to -3.23 and -3.13. Also, for the issuance of PUBs, no significant CAAR is observed. The results using the MSCI Europe index are summarized in Appendix E.

are highly statistically significant. The test statistics for the event window -10;30 of Boehmer et al. (1991) and Kolari and Pynnonen (2011) are t = - 3.84 / - 3.71 for the constant mean return model and t = – 3.11 / - 3.01 for the market model. As before, the CAAR is statistically not different from zero for firms issuing PUBs. Also, the CAAR for firms issuing PPBs is statistically different from those issuing PUBs in a two-tailed t-test (t = - 2.58) and in a Wilcoxon ranksum test (t = - 2.62). Compared to Section 4.1 and using the market model (the constant mean return model), the negative CAAR for firms issuing PPBs increases only by a relatively small 0.08% (0.69%) from – 5.33% (-5.94%) to – 5.41% (- 6.63%) when covenant intensity is high. Additionally considering the normal return calculations using the MSCI Europe and the market model (see footnotes 37 and 42), the abnormal return becomes less negative and goes from -5.40% to -5.03%. The data thus suggests the evidence for higher abnormal returns with high covenant intensity appears to be spurious. If abnormal returns are not primarily driven by high covenant intensity, then financing covenants might affect the CAAR. This is assessed in the next paragraph.

4.3 Financing covenants and announcement returns

Financing covenants are observed in 41% of all PPB issues but only in 18% of PUB issues (see **Table 1**). As shown by Böni et al. (2019), financing covenants are generally attached to bonds with high covenant intensity and it is very rare that such covenants are found in bonds with low covenant intensity. For the used sample, the average covenant intensity for PPBs with financing covenants attached amounts to 12.5 (n = 57). PPBs without financing covenants attached have a covenant intensity of 5.75 (n = 80), on average. Distinguished by PPBs with (without) financing covenants attached, the difference in covenant intensity amounts to 6.7 covenants and this difference is highly statistically significant in a student t-test (t = 12.27). This difference in the frequency of financing covenants might be an indicator of financing frictions that cause a wealth transfer from equity holders to bondholders. As Smith and Warner (1979) find in their analysis on this type of covenants (p. 137): “If, as the firm’s opportunity set evolves over time, new investments must be financed by new equity issues or by reduced dividends, then with risky debt outstanding part of the gains from the investment goes to bondholders, rather than stockholders. Those investments increase the coverage of debt, and reduce the default risk borne by the bondholders. […] They result in an increase in the value of outstanding bonds at the expense of the stockholders."

To assess the wealth transfer hypothesis, I sort on bond issues with financing covenants attached to a bond.[70] A financing covenant indicates a negative or restrictive covenant that places limitations on the amount of debt that the issuer can incur. A dummy variable taking the value of one, zero otherwise, is used to measure whether a financing covenant is attached to a bond issue. The results are given in **Figure 3** and **Table 7. Figure 3** plots the cumulative abnormal return for placement announcements from event day -10 to event day +30 for public and private placement bonds. The abnormal return is again calculated using the market model (constant mean return model). The announcement returns decrease remarkably to –6.8% (– 8.4%).[71] The CAAR of firms issuing PUBs is statistically not different from zero. The CAAR of firms issuing PPBs and using the parametric test of Boehmer et al. (1991) and the nonparametric test of Kolari and Pynnonen (2011) is highly significant at the 1% level using the constant mean return model and the market model. Using the market model (constant mean return model), the CAAR for the event window -10;+30 for firms issuing PPBs with a financing covenant attached and compared to Section 4.1 (**Table 5**) is higher by a significant 1.44% (2.44%). As in the previous analysis', the difference between the CAAR of PPBs and PUBs becomes consistently statistically significant only for longer event windows. However, using the market model, the 5% significance level is already reached for event window -10;+1. These results appear to confirm Smith and Warner's (1979) claim of a

[70] The analysis is based on a limit of indebtedness covenant that limits the issuer. In all but 1 case where the issuer is restricted, limitations on the amount of debt that an issuer's subsidiary can incur is also limited and this possibility is thus also captured.

[71] Using the MSCI Europe instead of the S&P500 index returns and the market model, the CAAR for private placement bonds and for the event window -10;+30 amounts to -6.07%. The test statistics for this event window and for Boehmer et al. (1991) and Kolari and Pynnonen (2011) are comparable to those using the S&P500 and both significant at the 1% level. Also, for the issuance of PUBs, no significant CAAR is observed. The results using the MSCI Europe index are summarized in the Appendix.

wealth transfer taking place when financing covenants are used. There appears to be a strong *ex ante* link between firm value and the use of limit of indebtedness covenants.

Overall, it appears that restrictive covenants and specifically financing covenants affect the firm value of firms issuing PPBs. For issuers of PUBs, no significant abnormal returns that are related to the use of covenants are observed. A potential explanation for this difference is a difference in covenant tightness between PPBs and PUBs. Measuring covenant tightness, however, exceeds the scope of this study and is more difficult to measure given the lack of standardization (see Demerjian & Owens, 2016, for a detailed discussion of measurement error challenges in trying to caputre covenant tightness). However, the data suggests that previous literature which finds that bond covenants, unlike loan covenants, might be written loosely and therefore be less effective in mitigating agency problems (Beneish & Press, 1995; Chen & Wei, 1993; Nini et al., 2009) is possibly not applicable to PPBs. It appears that investors and bond issuers put large effort into financial contracting in terms of mitigating agency problems.

4.4 The U-shaped relationship between covenant intensity and stock price response

Smith & Warner (1979, p. 121) propose "there is a unique optimal set of financial contracts which maximizes the value of the firm". One may therefore assume that the effect of covenant intensity on CAAR is not described by a linear relationship. To test this, I calculate the prediction for the CAAR from a linear regression of the CAAR on covenant intensity ("covscore") and covenant intensity squared ("covscore2") and plot the resulting curve. The model specification is described in equation (3):

$$CAR_{[-10;+30]i,t} = \beta_0 + \beta_1 covscore_{it} + \beta_1 covscore2_{it} + \in_{it} \tag{3}$$

$CAR_{[-10;+30]i,t}$ is the cumulative abnormal return, i is bond issuer, t is the announcement date, $\beta 1$ is the coefficient of the linear and β_2 the coefficient of the quadratic covscore variable, whereas ϵ_{it} is the error term. The fitted values for PUBs and PPBs are shown in **Figure 4**. A concave pattern with an optimum level of between 6 and 7 covenants attached to a PPB is observed. Lind and Mehlum (2010) propose that significant *β*'s resulting from the regression of a dependent variable on the independent variable and its square are not sufficient to establish a quadratic relationship. To provide additional evidence to this inverted U-shape, I follow two additional steps as recommended by Lind and Mehlum (2010) and add the results to **Figure 4**. First, I test for the overall presence of an inverted U-shape. Then I assess the significance of the steepness of the slopes at both ends of the data range. The segment of the inverted U-shape before the maximum (tipping point) should be positive and significant, with the segment beyond that point being negative and significant. For firms issuing PPBs, the overall test for the inverted U-shape as well as the lower and upper bound slopes are statistically significant. The lower bound slope for covscore is 0.02 and the upper bound slope is - 0.03. Next, I calculate the maximum and assess whether it falls within the data range. For covscore, the maximum is 6.47, with a 90% interval (calculated using Fieller's theorem) between 3.1 and 8.1, which is well in the covenant score range between 0 and 15. The CAAR goes from positive to negative at approximately 6.5 covenants attached to a PPB. According to the Lind and Mehlum (2010) test, one can be reasonably sure that the data describes an inverted U-shaped curve.

Next, I run the regression as in equation (3) and add industry and firm fixed effects. The result is presented in **Table 8**. As shown in column 1, the linear (quadratic) independent variables "covscore" ("covscore2") are highly statistically significant at the 1% level. Additionally, as recommended by Haans et al. (2016), I perform two additional tests: First, I split the data based on the empirically determined turning point of 7.25 an run two linear regressions. These should result in slopes consistent with the predicted shape of the curve. The results are given in **specifications 2 and 3 of Table 8**. I find the data range for the high covenant intensity (specification 3) above the empirically determined turning point is highly significant and has a higher adjusted R^2. Alternatively, conceptually as in Qian et al., (2010), I use the mean rather than the empirically determined turning point to split the sample (see **specifications 4 and 5 in Table**

8). I observe a negative coefficient significant at the 1% level. For the split sample of PPBs with covenant intensity below the mean value (specification 4), the coefficient is statistically not significant. Also, using the procedure as in Qian et al. (2010) improves the model fit largely as measured by the increasing adjusted R^2s of 30.1% for specification 5 as compared to 23.1% for specification 3. The Lind and Mehlum (2010) test results are given below Table 8.

Overall, the data provides strong support for the inverted U-shape between CAAR and covenant intensity.[72] It is conceivable that the upward sloping part of the inverted U is related to mitigating agency problems between bondholders and stockholders in bond contract design as proposed by Smith and Warner (1979). This explanation would be consistent with Reisel (2014) or Bradley and Roberts (2015), who find that the use of covenants reduces the cost of debt. Moreover, the inverted U-shape is consistent also with Böni et al. (2019) who find that the cost of debt for PPBs is reduced by including restrictive covenants but that that the relationship between spread and covenant intensity follows a U shape. The latter implies that the cost of debt is only reduced up to a certain level of covenant intensity, after which the cost of debt is increasing again. The downward sloping part of the inverted U appears to be related to the costs of covenants on the issuing firm. This cost-benefit tradeoff is fundamental to Smith and Warner's (1979) costly contracting hypothesis. A major cost is the restriction on managerial flexibility, which may outweigh the benefit from reduced agency conflicts. There is evidence that firms base their covenant choice on this tradeoff (see, for example, Begley, 1994, or Nash et al., 2003). A major cost of covenants is related to investment: Kahan and Yermack (1998) find that covenants might limit managerial discretion in the presence of investment opportunities. Anderson (1999) suggests that firms in high-growth, high-volatility environments do not accept covenants restricting dividend, investment, and financing policies because they are too costly.

An additional explanation for the downward sloping part of the inverted U can be derived from trade off theory: the level of debt impacts firm value by considering taxes and bankruptcy

[72] Additional tests of the quadratic relationship are beyond the scope of this paper. Critical issues and guidelines related to this topic are found in Haans et al. (2016).

costs (Leland, 1994). As evidenced in recent research, corporate capital structure stability is the exception and is temporary (Deangelo & Roll, 2015). Firms have different optimal leverage levels at different times, adjusting them regularly to maximize firm value. Covenants impact this adjustment process. Devos et al. (2017) empirically show that capital covenants significantly lower the speed of capital structure adjustment. They find that capital covenants delay the speed of adjustment by up to 86%. As in this study, Devos et al. (2017) use a covenant index and find that firms readjust their capital structure towards their target significantly slower when they have high covenant index values (more covenant restrictions). On average, they find that firms with the highest index values take 26 – 31 months longer or with a speed of adjustment that is 40 – 50% lower compared to firms with no covenants.

5 Other Explanations for Abnormal Returns

5.1 Other Explanations for Abnormal Returns

In this section, other potential explanations for abnormal returns of firms issuing PPBs are tested. I estimate cross-sectional equations and regress the CAR, as calculated by the constant mean return model, on the respective variables described below, using robust standard errors. The regression model is given in equation (4),

$$CAR_{[-10;+30]i,t} = \beta_0 + \sum_{j=1}^{K_1} \beta_{1j}\, covenant\ intensity_{ijt} + \sum_{j=1}^{K_2} \beta_{2j} creditrisk_{ijt} + \sum_{j=1}^{K_3} \beta_{3j} liquidity_{ijt} + \sum_{j=1}^{K_4} \beta_{4j} market\ conditions_{ijt} + \sum_{j=1}^{K_5} \beta_{5j}\, other\ controls_{ijt} + \beta_6 placement_{it} + \epsilon_{it} \tag{4}$$

where CAR is the dependent variable, estimated over the event window -10;+30, and i is bond issuer (firm), t is the announcement date. K_1 to K_5 are the number of independent variables within each group 1 through 5 (1: covenant intensity, 2: credit risk, 3: liquidity, 4: market conditions, 5: other controls), whereas β_{1j} through β_{5j} represent the coefficients for independent variable j within category 1 through 5. Placement is a dummy variable taking the value of 1 when a placement is a private placement, zero otherwise, and represented by β_6. Finally, ϵ_{it} is the error term. I control for year fixed effects and industry fixed effects in all specifications. Additionally, I use the entire rather than the split sample and add several interaction terms. The variables are as defined previously are described here again for completeness and independence of the chapters:

Credit risk. Smith & Warner (1979) argue that private placements are more likely to be issued by riskier firms than is public debt. As is shown in **Table 1 and** measured by the mean (median) leverage ratio, that of firms issuing PPBs is 29% (27%) and is by 3% (5%) higher than that of firms issuing PUBs, i.e. 26% (22%). Also, the rating score is worse by approximately one notch. It is therefore possible that differences in risk explain the differences in abnormal returns. To gauge for this effect, I use a score proxying for firm rating, which is a frequently used measure for credit risk in empirical research (see, for example, Campbell & Taksler, 2003; Collin-Dufresne et al., 2001; Elton et al., 2001; Longstaff et al., 2005). I use the most recent financial data preceding a bond issue[73] and calculate a score proxying for the credit rating ("rating_score") of the issuer based on credit model 2.6 (henceforth "CM") of S&P Global Market Intelligence (Standard & Poors, 2016). The model output consists of a letter grade score from AAA (with a numerical value of 1) to CCC or lower (with a numerical value of 18) and represents a company's standalone credit risk. CM is a statistical tool estimating S&P Global Ratings to assess the credit risk of corporates. A more detailed description of the model is given in **Appendix B**. Since equity prices are

[73] These are quarterly, half-year or annual statements published prior to the bond issue and available on S&P.

significantly affected by short-term information, I consider this credit risk proxy to be more unbiased than a rating of an agency. The advantage of using this score is that it is based on recent financial data and measures the financial condition of a bond issuer whilst traditional ratings measure the creditworthiness of a corporation over long investment horizons (Alp, 2013) and tend to be updated slowly (Cornaggia & Cornaggia, 2013). The used proxy, however, should not be confused with an agency rating as issued by S&P, Moodys or Fitch. CM aims to match the S&P–rating with a good performance, which is evaluated on an annual basis.[74] As in Reisel (2014) I use issuer rather than bond ratings because covenants have an impact on bond ratings, but not the issuer rating. Since ratings measure credit risk only broadly and since there is some variance of credit quality even within a rating category (Helwege and Turner, 1999), I additionally account for structural characteristics of debt issuers following the Merton (1974) model and use book leverage calculated as the ratio of total long-term debt to total assets of the issuer (“***leverage***”) as second proxy for credit risk. This measure is also used by Harvey et al. (2004), who assume that debt mitigates managerial agency costs. As in their study and as argued by Barclay et al., (2006), I use book leverage to measure the ratio of debt to a firm’s assets in place.

Market liquidity. Next, I use two measures of liquidity: (1) a decomposition of sovereign bond yields into a credit and a liquidity component and the resulting spread to proxy for bond market liquidity (“bml”) and (2) Pástor and Stambaugh’s (2003) measure to proxy for equity market liquidity (“eml”). For the first, I decompose bond spreads into credit and liquidity premia. This concept is based on a methodology used for bond pairs with equal credit risk but different liquidity and was applied also by Longstaff (2004), Ejsing et al. (2012), Monfort and Renne (2014) or Helwege et al. (2014). The idea is that credit risk is issuer-specific, whilst liquidity is bond specific. I identify liquidity-pricing effects by exploiting the information contained in spreads between bonds with the same credit risk but different liquidity. I use the 7 years maturity Refcorp-

[74] The CM performance is measured in percent of exact rating matches, +/- 1 notch, +/- 2 notches and +/- 3 notches deviation from the S&P Global Ratings. The last available validation was done in July 2016 and has resulted in 22% exact matches, 56% matches within 1 notch, 78% within 2 notches and 88% within 3 notches.

bonds to proxy for market liquidity in USD and use data from Bloomberg. Refcorp (Resolution Funding Corporation) is a government agency, fully collateralized by Treasury bonds and full payment of coupons is guaranteed by the Treasury. The spread between the yield to maturity on bonds issued by Refcorp, a US government agency, and the more liquid US government benchmark rate is used. Following Longstaff (2004), I subtract the yields on Refcorp bonds from the riskless maturity matched USD rate on the issue date. While the objectives and the core businesses of Refcorp are different, both of them have explicit and full debt guarantees from their sponsoring state. Thus the bonds issued could default only if the corresponding state itself defaults, which means that the credit risk of Refcorp equals the credit risk of the US. To capture the market liquidity preceding a bond issue, I calculate a 90-day moving average of the spread between the 7 year Refcorp-bond to the respective government bond benchmark for each issue date and create a variable to gauge for bond market liquidity ("***bml***").

As evidenced by Huang et al. (2015), a drop in stock liquidity also increases a firm's credit risk by increasing the default boundary. Additionally, Brogaard et al. (2017) evidence a relationship between stock liquidity and firm bankruptcy. Abnormal returns could therefore be affected by equity market liquidity ("**eml**"). I therefore include the monthly aggregate liquidity measure of Pástor & Stambaugh (2003) to account for stock market liquidity, reported in the Wharton research data services (wrds) platform.[75] This aggregate liquidity measure provides a monthly cross-sectional average of individual stock liquidity measures and indicates volume-related return reversals arising from liquidity effects.[76] The aggregate average market liquidity of the month prior to the bond issue is matched with each issue date.

Market conditions other than liquidity might affect firm values. Managers are able to time the markets and issue equity when the stock of the firm is high or overvalued (Baker & Wurgler,

[75] https://wrds-web.wharton.upenn.edu/wrds/

[76] The basic idea of Pástor & Stambaugh (2003) is that (p. 647) „orderflow, constructed […] simply as volume signed by the contemporanous return on the stock in excess of the market, should be accompanied by a return that one expects to be partially reversed in the future if the stock is not perfectly liquid. The greater the exprected reversal for a given dollar volume, the lower the liquidity.

2002). Hale and Santos (2008) show, for example, that firms time their bond issues to avoid recessionary periods and take advantage of favorable market conditions. It is conceivable that managers time the markets also when issuing PPBs and that this affects abnormal returns. To capture ups and downs in the economy I follow Alp (2013) and use real GDP growth rates[77] for a period of 360 ("***gdp_360***") calendar days prior to the bond issue.[78] Furthermore, as in Chen et al. (2007) or Campbell and Taksler (2003) I include the risk-free rate of the benchmark bond ("***benchmark***") and the difference between the 10-year and 2-year Treasury rates to account for the level and the slope of the yield curve ("***slope***"). Like Collin-Dufresne et al. (2001), I interpret "slope" as an indicator of the overall state of the economy. Merton (1974) predicts that equity volatility impacts the likelihood of reaching boundary conditions for default. To capture changes in aggregate equity market volatility, as for example in Collin-Dufresne et al. (2001), I use the CBOE VIX-index ("***vix***") values. They correspond to a weighted average of eight implied volatilities of near-the-money options on the OEX (S&P 100–Index). Additionally, as in Acharya et al. (2007), I measure if an industry is distressed by the return of the index representing the issuer's industry. Following Cremers et al. (2008), I calculate the index return over the past 180 days prior to a bond issue. I use the MSCI Europe Index family and its industry specific derivatives to calculate this 180 day return prior to the announcement of a bond issue ("***mscii_180***"). As proposed in Longstaff and Schwartz (1995), Collin-Dufresne et al. (2001) or Campbell and Taskler (2003), index returns are interpreted as the overall state of the economy.

Other controls. As **Table 1** indicates, firms issuing PPBs are smaller than firms issuing PUBs. Announcing the issue of a PPB might convey information about the inability of a small firm to launch a public bond (PUB), eventually explaining the negative abnormal returns. To determine,

[77] I use European GDP data from Eurostat (http://ec.europa.eu/eurostat/web/national-accounts/data/main-tables adjuested for inflation given by the Harmonised Index of Consumer Prices (HICP) oft he Euro area compiled by Eurostat and the national statistical institutes. Details can be retreived from http://ec.europa.eu/eurostat/web/hicp/data/database .

[78] A variable capturing 180 days was also tested but found to be statistically insignificant.

whether differences in firm size can explain differences in abnormal returns, I control for firm size measured by the logarithm of total assets ("**logsize_a**"). **Maturity:** According to Carey et al. (1993) investors in private debt have strong credit monitoring units and exercise control through covenants. Covenants are used to encourage monitoring but are, however, not perfect contractual mechanisms for ensuring monitoring and control (Rajan & Winton, 1995). It is conceivable that firms with larger information asymmetries issue more short-term debt (Barclay & Smith, 1995) to mitigate agency costs and that the maturity of debt impacts abnormal returns. A firm may attempt to mitigate agency costs through its choice of maturity of its bonds. This reduces the underinvestment problem and the asset substitution problem.[79] **Top-tier Arranger:** Moreover, since firms that issue PPBs use top tier banks more than firms issuing PUBs (in 54% versus 37% of all events), I investigate whether the involvement of a top tier arranger ("**top_tier**") impacts abnormal returns. McCahery and Schwienbacher (2010) find that the reputation of top tier arrangers leads to higher spreads in the private debt market, as opposed to public debt issues. It is conceivable that the arranger quality conveys information to the market and that higher costs of debt lead to negative abnormal returns. I make a distinction between top tier arrangers and other arrangers and define a bank as a top tier arranger in a particular year if it was one of the three biggest players in the calendar year prior to the issue analyzed. Data are from Bloomberg and the market share of all the market participants in the European bond market for each year based on their total annual placement volumes is calculated. The variable takes the value of one, zero otherwise, if at least one of the arrangers of a bond is on the list of the three biggest arrangers in the year before the considered bond issue.[80] **Firm age.** Next, as in James and Wier

[79] According to Nash et al. (2003), the underinvestment problem is lessened by shorter maturities because the longer maturity of a bond provides a greater period for profitable investments and rejected by managers acting in shareholders' interest. The asset substitution problem is reduced because increasing the variance of asset values is worth less with a shorter term option on these assets.

[80] This way of identifying top tier banks is the same as that of Megginson and Weiss (1991) and Asker and Ljungqvist (2005). Contrary to them, Fang (2005) applies only one single league table consisting of all deals of the complete time period considered, resulting in a constant list of top tier banks. Given the observed annual ranking changes and the mergers and acquisitions among banks, I apply an annual table. Megginson and Weiss (1991) measure reputation with market shares and do not transform the league tables into a

(1990), Helwege and Liang (1996), Krishnaswami et al. (1999) or Maskara and Mullineaux (2011), I include the firm's age, defined as the number of years since inception, to proxy for the degree of ex ante information asymmetry. The intuition is that younger firms have limited financial histories and a greater degree of information asymmetry. Following Diamond (1991), age proxies for the quality of the credit record of a firm and is a predictor of future actions of a borrower. The logarithm of firm age is used ("**log_age**"). **144a-Registration.** Prior studies make a distinction between 144A registered bonds (Fenn, 2000; Chaplinsky & Ramchand, 2004; Arena, 2011) and non-144A registered bonds (Kwan & Carleton, 2010; Arena, 2011). The 144A debt market can be used to issue sub-investment grade debt that can be subsequently registered (Fenn, 2000) and firms issuing 144A debt are found to be different from those using non-144A, traditional private debt (Arena, 2011). I control for a difference in abnormal returns by introducing a dummy variable ("**a144**") taking the value of 1 if a bond was issued under 144A registration rules, zero otherwise. **Loan purpose.** James (1987) finds a significant decrease in share price for privately placed debt used to refinance bank loans. To test for this possibility, the use of proceeds of all bond placements is downloaded from Bloomberg and S&P and analyzed. A dummy variable taking the value of 1 is used to identify those PPBs that use the proceeds from the bond placement to refinance other debt, zero otherwise ("**ref**"). Of the 137 firms issuing PPBs, 56 or approximately 41% fall into this category. **Growth options:** Nash et al. (2003) find that firms with high growth opportunities are less likely to include financing covenants in their bond contracts. I gauge an issuer's growth options following Nash et al. (2003) and Barclay and Smith (1995) and use the ratio of the market value to the book value of the firm ("**mtb**").[81] Finally, I include a dummy variable equal to 1, if a bond issue has a call option ("**call**") attached, zero otherwise.

dummy variable. The advantage of having a continuous variable, which does not impose an arbitrary cutoff level, has the drawback that it does not allow to adapt the variable for possible self-selection bias, which requires a binary variable.

[81] More precisely I use this ratio as calculated in Nash et al. (2003, p. 209) and equal to the book value of assets minus the book value of equity plus the market value of equity divided by the book value of assets.

Starting with the baseline regression in specification 1, the regression model is extended by analyzing how proxies for credit risk (specification 2), market liquidity (specification 3), market conditions (specification 4) and other controls (specification 5) impact the CAAR of firms issuing PPBs or PUBs. Specification 6 shows the full empirical model as in equation (4). Specification 7 imposes a restriction on covenant intensity and assumes its impact on public placements is equal to zero. Finally, specification 8 uses factor analysis and tests whether a monitoring and a financing factor impact the CAAR for firms issuing PPBs or PUBs.

The results are presented in **Table 9.** The placement variable is negative and highly statistically significant at the 1% level across all eight specifications with the exception of specification 5, in which the placement variable is significant at the 5% level. Moreover, whilst the use of covenants appears not to affect the CAR of firms issuing PUBs, it does affect the CAR of firms issuing PPBs. The linear interaction variable ("covscoreXplacement") is highly significant at the 1 % level in specifications 1 through 4, significant at the 5% level in specification 7 and marginally significant at the 10% level in specifications 5 and 6. The quadratic interaction variable ("covscore2Xplacement") is significant at the 5% level in specifications 1, 4 and 7, marginally significant in specifications 2 and 3 and not significant in specifications 5 and 6. The limit of indebtedness factor ("f2_loi") in specification 8, however, is not significant. No statistically significant relation between the CAAR and credit risk, as proxied by rating_score and leverage (specification 2) or liquidity, as proxied by bond- and equity market liquidity (specification 3). is found. Bond market liquidity becomes marginally significant in specification 6, however, indicating that this market condition might also affect the CAR.

Specification 5 shows the impact of market conditions on the CAAR. No statistically significant relationship between the CAAR and the risk-free ("**benchmark**") rate or the slope of the yield curve ("**slope**") is indicated. Equity market volatility ("**vix**") is statistically significant at the 5% level and positive, the state of the issuer industry ("**mscii180**") is only marginally statistically significant at the 10% level and negative. All else equal, a one standard deviation change in equity market volatility (s = 8.3) reduces the CAAR by an economically important 5.0%, whilst a +/- 5% return on the index creates a -/+ 0.7% change in the CAAR. It appears somehow counter-intuitive that higher aggregate equity market volatility should decrease negative abnormal returns, since it increases the likelihood of reaching boundary conditions for default (Merton, 1974). However, it is conceivable that idiosyncratic, rather than aggregate, equity market volatility impacts abnormal returns differently. A research topic left for further research.

Of the other controls (specification 5), the variables that affect abnormal returns are the option of a firm to retire bonds prior to their maturity ("**call**") and the 144A-registration ("**a144**"). The significance and economic importance of the right to retire a bond prior to its maturity supports the assumption made in Section 4.4 that high covenant intensity may reduce managerial flexibility, exacerbate investment or reduce the speed of capital structure adjustment. A call option can, for example, eliminate underinvestment problems in that it grants the shareholders the right to retire debt when it encounters positive NPV projects. By execution of the call and subsequent investments for which the firm may issue new debt, the value of new investments and the related benefits of the incremental project are acquired by the shareholders (Nash et al., 2003). This argumentation is in line with Smith & Warner (1979), who find that restricting future debt issues creates a wealth transfer from stockholders to bondholders: financing new investments by new equity issues or by reduced dividends, with risky debt outstanding part of the gains from the investment goes to bondholders, rather than stockholders. Such investments increase the coverage of debt, and reduce the default risk borne by the bondholders. The mentioned distinction between 144A registered bonds and non-144A registered bonds as measured by the respective dummy variable is only marginally significant at the 10% level and positive. This may indicate that firms issuing 144A debt are in effect different from those using non-144A, traditional private debt (Arena, 2011). A firm issuing 144A-registered bonds appears to show less negative abnormal returns by 4.7%.

Turning to **specificaton 8 in Table 9**, the linear and the squared (X^2) covenant intensity variables are replaced by two factors and interacted with the placement variable. A monitoring factor ("**f1_mc**") and a financing factor ("**f2_loi**") are used. I refer to Böni et al. (2019) and use the factor analysis methodology described in their paper to create and analyze the dimensions in the use of covenants.[82] The first factor (monitoring covenants) interacted with placement is statistically significant at the 5% level and positive, suggesting that monitoring per se does reduce agency costs and abnormal returns. Rather than the mere use of covenants, it appears to be covenant intensity that affects abnormal returns negatively. The second factor (financing) is negative and has the right sign. However, it is statistically not significant. One might argue that the factor analysis as in specification 8 contradicts the results presented earlier in this paper. However, as is shown in Böni et al. (2019), it is difficult to separate high covenant intensity from financing covenants. They find that if a financing factor ("**f2_loi**") is attached to a bond, then for 96 % of all bonds issued, on average, there is also a monitoring factor ("**f1_mc**") attached to such bond. Contrary to this, if a monitoring factor ("**f1_mc**") is attached to a bond, then, only in 47% of all bond issues on average is there a financing factor attached to such bond. In the sample of this paper, for bonds with more (less) than the median number of 8 covenants attached to a bond, 53% (5.8%) have a financing covenant attached. Given this confirmed logical ordering, the results shown in specification 8 do therefore fail to support but not necessarily contradict the results presented earlier in this paper.

6 Robustness Tests

6.1 Potential inference from event date clustering

Boehmer et al. (1991) claim their test is robust to cross-sectional correlation of returns due to event day clustering.[83] Also, the nonparametric test of Kolari and Pynnonen (2011) is

[82] Böni et al. (2019) investigate the pricing of PPBs. Using factor analysis, they find a monitoring and a limit of indebtedness dimension in the use of covenants. The first is negatively, the latter positively related to spread. It is argued that limit of indebtedness covenants exacerbate flexible firm investment and efficient capital structure adjustment and therefore increase spread, whilst the monitoring factor decreases spread given an improvement in monitoring and a reduction in agency costs..

[83] Boehmer et al. (1991, p. 268) comment their simulation results and conclude that they "are essentially unaffected by the presence of event-date clustering.".

considered to be robust to event day clustering. In 30 out of 325 events, the aggregation of abnormal returns takes place in overlapping calendar time. 11 of these 30 events are private placements. Additionally to the mentioned tests, it is ruled out that the covariances across securities affect the presented results in material ways by dropping events that potentially create event date clustering. Of the sample, 11 PPBs and 19 PUBs are issued on identical trade days. These observations are dropped from the sample and the results are compared to those reported in Section 4.1. Using the market model / the constant mean return model as in 4.1, the CAAR -10;30 without (with) the clustering observations amounts to 5.22% (5.33%) / 5.54% (5.94%). The statistical significance using the Boehmer et al. (1991) test remains highly significant for both estimation methods and is t = - 3.77 (- 4.09) / - 3.58 (- 3.74) for the constant mean return model / the market model with (without) dropping clustering events. Using the non-parametric test of Kolari and Pynnonen (2011), the test remains highly significant for both estimation methods and is t = - 3.62 (- 3.85) / - 3.46 (- 3.52) for the constant mean return model / the market model with (without) dropping clustering events. It can be concluded that the abnormal returns do not deviate in a material way from those reported earlier and neither does statistical significance of the CAAR. Event date clustering appears not to affect the abnormal returns in material ways.

6.2 Controlling for confounding events

The next robustness test is related to confounding events that may occur within the event window. The key development feed of S&P (Compustat) is used to retrieve a structured summary of material news and events that may affect the market value of securities.[84] I control for 24 potentially confounding events described in detail in **Appendix C** and for the three scenarios (all

[84] This feed monitors over 100 key development types. Sources include newswires, newspapers and disclosure wires such as Reuters, Dow Jones, Comtex, Regulatory News Service, The Associated Press, Bloomberg Business News, CNN and CBS in addition to content from local providers.

bond issues, bond issues with high covenant intensity and isues with limit of indebtedneses covenants attached). The results are presented in **Table 10**.

First, following Ball and Brown (1968) I consider the information content of earnings announcements. Second, as in Fama et al. (1969), I control for simultaneous dividend increases or decreases, since these are expected to impact stock prices (Dhillon & Johnson, 1994). Unexpected dividend increases or dividend initiations usually result in a positive stock market response explained by a wealth redistribution between stockholders and bondholders or the information content of such announcement (Dhillon & Johnson, 1994).[85] Additionally, the ex-dividend date is considered, since dividend payments directly impact the value of a stock (Ingersoll, 1977). Third, price effects of merger announcements (Manne, 1965; Jarrell & Paulsen, 1989; Eckbo, 1983) and, fourth, simultaneous financing announcements such as for example seasoned equity offerings (SEOs) in the event window are also controlled for (Mikkelson and Partch, 1986; Asquith and Mullins 1986; Masulis and Korwar, 1986; Carlson et al., 2006; Lyandres et al., 2008 or Johnson et al., 2018). Finally, as in Johnson et al. (2017) analyst recommendation changes within the event window are used to control for confounding events. Eliminating all bond issues with confounding events reduces the number of observations too much. I therefore follow Nikolaev (2017) and create a set of dummy variables to control for each event type and verify the robustness of the results by dropping observations subject to these confounding events.

Table 10 contains the results of the analysis, based on the constant mean return model. As in Harvey et al., (2004), I verify that the results hold in magnitude and significance when confounding events are removed from the analysis. The cross-sectional t-test as in Brown and Warner (1980) is used to test the null hypothesis that the CAAR is equal to zero. Panel A shows the CAAR for bond issues with no restrictions, Panel B for bond issues with high covenant intensity

[85] From an agency theory perspective and according to Jensen and Meckling (1976), the distribution of cash reduces empire building and avoids engagement of management in negative NPV projects. Cash distribution by paying dividends according to Jensen's (1986) free cash flow theory suggests that unexpected dividends should cause a positive reaction in stock markets. From an information signaling standpoint, several researchers view unexpected divident changes as a signal sent by the managers about a firm’s future profitability (see Kalay, 1980; Miller & Rock, 1985). For a recent empirical study evidencing the positive relationship between dividend announcements and stock returns see Tsai and Wu (2015).

and Panel C those with financing covenants attached. As evidenced in **Table 10**, dropping confounding events does not materially affect the abnormal returns presented in prior Sections and leaves the conclusions unchanged. In absolute terms, the CAAR remains comparable in magnitude and the t-statistics significant in all cases of dropping observations, mostly at the 1% and 5% level, for some few observations, the significance drops to the 10% level. However, it appears that the estimated CAAR is robust with respect to the tested confounding events and that these events do not invalidate the results.

6.3 Other robustness tests

To make the study comparable to those using the S&P 500 value weighted index instead of the equal weighted index when calculating market model abnormal returns, it is examined whether the results are sensitive to estimating normal returns with this alternative benchmark. Using the S&P 500 value weighted (equal weighted) index results in an almost identical CAAR of - 5.34% (- 5.33%). Also, statistical significance using the parametric test of Boehmer et al. (1991) / Kolari and Pynnonen (2011) remains at the 1% level with t-values of – 3.73 (- 3.74) / - 3.52 (- 3.52) . It appears that using the value weighted index instead of the equal weighted version does not affect the results of the study.

Moreover, the study controls for effects from non-synchronous trading. As is explained in MacKinlay (1997, p. 35), such effects can “arise when prices are taken to be recorded at time intervals of one length when in fact they are recorded at time intervals of other possibly irregular lengths”. Since I employ daily closing prices from Bloomberg and since these closing prices generally do not occur at the same time each day, they are not equally spaced at 24-hour intervals. This nontrading effect can induce biases in the moments and co-moments of returns. I apply the method of Scholes and Williams (1977) and use their consistent estimator of beta to recalculate the market model based on the value weighted version of the S&P 500 index. The results are almost unchanged: the CAAR increases slightly to – 5.48%, remaining highly statistically significant at the 1% level with t-values using Boehmer et al. (1991) / Kolari and Pynnonen (2011) of – 3.83 / 3.62.

It is conceivable that pre-event window returns affect issue characteristics, such as for example the use of covenants. In order to control for potential endogeneity problems arising from this, the CAAR for firms issuing PPBs is estimated using the +1;30 event window as the dependent variable. The results do not change in material ways. The CAAR using the market model amounts to –4.27%, again highly statistically significant at the 1% level with t-values using Boehmer et al. (1991) / Kolari and Pynnonen (2011) of – 3.46 / 3.26.

7 Are Abnormal Returns due to Uncertainty about Credit Risk?

In the previous analyses, I implicitly assume that debt covenants and specifically those attached to PPBs convey information to investors. All other explanations for abnormal returns and the following robustness checks were based on firm characteristics and market data. While this may well proxy the information available to investors at or around the event date, from a contracting perspective, there may be additional information that explains stock price reactions. I therefore employ two additional tests to check on the robustness of the results, i.e. (1) a proxy for reporting quality information available to investors at the event date and (2) Altman's (1977) Z-score to proxy for bankruptcy risk.

First, financial information reporting quality plays a significant role in the determination of bond ratings (Kraft, 2015) and covenants in debt contracts are frequently written on this information (Leftwich 1983; Smith and Warner 1979). Moreover, research shows that reporting quality affects how covenants are used (Costello & Regina, 2011; Graham et al., 2008). Also, reporting quality affects investor decisions and securities pricing (Minnis, 2011). Because investors rely on reporting quality, it may affect abnormal returns. Consequently, I argue that a proxy for reporting quality that is easily understandable to investors and available at the event date may affect stock price reactions. Akins (2018) shows that better reporting quality is directly associated with less uncertainty about credit risk as captured by disagreement among the credit rating agencies. As in Morgan (2002) or Akins (2018), I employ the pattern of disagreement between credit rating agencies (CRAs) to proxy for reporting quality.[86] This disagreement is, in part, driven by uncertainty about credit risk (Morgan, 2002). I use the historical credit ratings of S&P and Moody's and their split over the bond issuers to proxy for uncertainty about credit risk. The data are from Bloomberg. Of the 325 bond issuers, I can retrieve 222 ratings from S&P and 65 from Moody's. This first analysis entails a loss of observations for which I can calculate the dispersion in credit ratings. I map the ratings as assigned by the agencies to a numerical scale, a lower number representing a higher credit rating (1 = AAA = Aaa, 2 = AA+ = Aa1, etc.). The difference in the numerical value (**"cr_dispersion"**) is interpreted as a proxy for uncertainty about credit risk as in Akins (2018). The dispersion for those issuers rated by both CRAs (n=60) amounts to an average (median) 6.2 (7) notches, to 5.9 (7) notches for firms issuing private bonds and 6.6 (7) for those issuing public bonds. This rating disagreement appears to be important. Testing the difference in mean abnormal returns in a two-tailed student-t (ranksum) test, t-(z-) values remain well below one for the full sample (n=60/309, t=0.26, z=0.51), for firms issuing private (n=30/128, t=-0.96, z=-1.00) and firms issuing public bonds (n=30/181, t=0.85, z=1.17). I also use Pearson's chi-squared test to evaluate if the median difference in abnormal returns arose by chance and can not reject this for all firms, firms issuing private and firms issuing public bonds with $X^2(1)$ = 0.70 (p = 0.40), 0.70 (p = 0.40) and 0.59 (p = 0.44). Next, I am interested whether "**cr_dispersion**" affects abnormal returns. I run OLS regressions in the form as in the previous Section. Controlling for the dispersion in credit rating between CRAs in specification (2) of Table 11 appears to impact the regression results: while the dispersion variable is statistically not significant, the interaction with placement (**"cr_dispersionXplacement"**) is significant at the 5% level. CRA dispersion is positively related to abnormal returns. An increase in dispersion (increase in uncertainty about

[86] Analyst recommendations and the dispersion in such recommendations may also serve as a meaningful control. However, it was not able to retrieve reliable data on the dispersion of analyst recommendations for the sample period. Instead, I used the number of analysts covering a bond issuer. In a student t-test and in the cross-section, the mean number of analysts for firms issuing PPB (PUB) is 22.65 (19.10) on average and lower by 3.5 for firms issuing PPBs, this difference statistically significant at the 1% level. Including this control into the OLS regression analysis as in Table 11, however, does not reveal any significant results, these results therefore remain untabulated for brevity.

credit risk) explains parts of the negative abnormal returns and renders it less negative by an important 2.5% per notch of rating dispersion and the adjusted R^2 for the smaller sample, as compared to the baseline in specification (1), increases to 21.3%. However, dispersion does not entirely explain abnormal returns, as the placement variable remains significant, and is now larger in magnitude when compared to specification (1). Also, covenant intensity (squared), interacted with placement, remains statistically significant. However, the data suggests that CRA dispersion, or uncertainty about credit risk, does partially explain abnormal returns. However, the effect from the use of covenants for a private bond with, for example, ten covenants attached is still significantly larger than the effect from CRA dispersion. Estimating the abnormal return from specification (2) and an average CRA dispersion of 6.2 notches, this dispersion affects the abnormal return by approximately +15% (2.5% X 6.2). The effect given ten covenants attached to a private bond is – 133% (12.4% - 1.45%X100). This effect is very large and it is likely the result is spurious as additional control variables have been excluded from specification (2) to avoid model overspecification.[87] Controlling for CRA dispersion, it appears to explain parts of the abnormal return. A larger sample would be needed, however, to confirm this finding.

Next, Altman's Z-score (**"zscore"**) index (Altman, 1977) is used as a proxy for an issuer's bankruptcy risk. [88] It is computed as in Denis and Mihov (2003).[89] I include the score in specification (3) of Table 11. Z-score used as an ordinal variable is insignificant.

In an additional analysis I create an indicator variable equal to one when Altman's Z-score is smaller than the median score of 2.75, that is when the firm is at risk of bankruptcy (**"zscore_low"**). The result is shown in specification (4). The adjusted R^2 of 18.8% is higher than that of the baseline regression in specification (1). Z-score_low is significant at the 5% level.

[87] Adding additional variables that are significant in specification (1) individually or jointly to specification (2) does not substantially change this finding.

[88] This proxy has been used in numerous studies, for example for the evaluation of the performance of long-run stock returns following issues of public and private debt in Dichev and Piotroski (1999).

[89] Z = 1.2 (working capital / assets) + 1.4(retained earnings/assets) + 3.3(ebit/assets) + 0.6(market cap/debt)+0.999(revenue/assets).

However, high bankruptcy risk appears to explain abnormal returns for all bonds, and not specifically for private bonds. The magnitude of the bankruptcy risk measure (+7.35%) compared to that of covenant intensity and when using the cross-sectional mean of 7.5 covenants (+26%) suggests the use of a covenant based explanation of abnormal returns.

In specifications (5) and (6), I control for effects when splitting the sample into observations for PPBs and PUBs. The adjusted R^2 increases to 33% for the private bond sub-sample in specification (5) and the covscore (squared) variables are significant at the 1% and 5% level respectively. Contrary to this, the covscore (squared) variables in the public bond sub-sample have not much explanatory power with respect to abnormal return and remain insignificant with t-values well below one. The results suggest that in fact, covenant effects are observed for firms issuing private, but not for firms issuing public bonds. Bankruptcy risk as proxied by zscore_low shows up insignificant but with a t-value of 1.29. Using it as point estimate, it would explain approximately 6.1% of

In summary, controlling for uncertainty about credit risk does not change the main findings. The data suggests the use of covenants attached to privately placed bonds conveys information to investors ex ante, while, on the contrary, it does not convey information to investors when bonds are placed publicly.

8 Conclusions

The main contribution of this study is twofold: First, is shows that use of covenants attached to privately placed bonds conveys information to investors ex ante. On the contrary, covenant use appears not to convey information when bonds are placed publicly. Second, the stock price response to issuing private bonds is negative in the cross-section. Privately placed bonds are much like bank loans with respect to ownership concentration (typically a few institutional investors) and show increased investor protection given their high covenant intensity. As with other private financings, one could then expect positive abnormal returns. The positive stock response to announcements of private financings is well documented and typically rationalized as a reflection of valuable monitoring and screening services provided by banks (Fama, 1985; James, 1987) or other private lenders such as, for example, lenders with high reputation (Billett et al., 1995) or syndicates with few lenders (Preece & Mullineaux, 1996). Contrasting this event-study driven prior research, I find that private bonds differ in significant ways and result in negative stock returns when announced.

Private bonds with below average covenant intensity or no financing covenants attached show abnormal returns that are not statistically significant. Additionally, a concave relationship between covenant intensity and the cumulative average abnormal return (CAAR) is evidenced, suggesting that the benefits of including restrictive covenants in debt contracts diminish after a certain level. It is suggested that negative abnormal returns root in the use of financing covenants attached to privately placed bonds. The CAAR also appears to be affected by the registration of the bonds. For firms issuing A144-registered bonds, the abnormal return is less negative than that of firms issuing non-registered bonds and the significance of the CAAR is only marginal for the first, whilst it is high for the latter group.

Recent prior studies show that a lack of information about future economic events and their consequences for the borrower's creditworthiness are positively related to covenant intensity (Demerjian, 2017) and that monitoring mechanisms, such as the use of covenants, are positively related to renegotiation intensity (Nikolaev, 2017). It appears investors do not place value on a firm's option for flexible debt renegotiation when placing bonds privately.

Left for future research is the question, whether other factors may explain abnormal returns. These may also be due to the cost of reducing the speed of capital structure adjustment (see Byoun, 2008 and Devos et al., 2017), which may be lowered by the inclusion of covenants into debt contracts, may result in abnormal returns.

9 Tables

Panel A: Bond Characteristics

	Public				Private				Difference		
variable	mean	sd	median	N	mean	sd	median	N	Δ	t	z
maturity	9.48	6.21	7.52	188	9.06	4.78	8.02	137	**-0.65**		
amount	1027.38	1561.33	500.00	188	1624.21	3243.80	750.00	137	**596.83**	***	***
top_tier (0/1)	0.37	0.48	0.00	188	0.54	0.50	1.00	137	**0.17**	***	***
covscore	7.01	3.84	8.00	188	8.54	4.58	10.00	137	**1.54**	***	***
loi_covenants (0/1)	0.18	0.38	0.00	188	0.41	0.49	0.00	137	**0.24**	***	***

Panel B: Firm Characteristics

variable	mean	sd	median	N	mean	sd	median	N	Δ	t	z
age	58.31	47.94	38.00	181	61.93	54.12	42.00	122	**3.61**		
size_a	42911	63531	12152	187	23587	47218	8383	132	**-19324.82**	***	**
size_r	20483	25038	10165	187	11983	19616	5276	135	**-8499.37**	***	**
leverage	0.26	0.15	0.22	181	0.29	0.14	0.27	129	**0.04**	**	***
profit	0.13	0.22	0.15	187	0.15	0.20	0.15	135	**0.02**		
rating_score	8.64	3.50	8.00	183	9.61	2.73	9.00	131	**0.97**	***	***
equity	21821.77	41411.85	5167.44	188	7269.74	11631.43	2646.17	135	**-14552.03**	***	***
market cap	27285.01	35059.19	11424.20	186	11694.67	15587.85	6086.46	136	**-15590.34**	***	***
market to book	1.99	1.79	1.46	180	2.35	3.56	1.63	128	**0.37**		

Table 1: Descriptive Statistics on Private (PPB) over Public Placement Bonds (PUB)

This table provides descriptive statistics for bonds and firms characteristics for a sample of private and public placement bonds issued in Europe from 2002 through 2015. Bond characteristics are reported in Panel A, firm characteristics in Panel B. For variable definitions, see Appendix A. Δ / t- and / z-values denote the difference between PPB over PUB / t-statistics / and Wilcoxon rank sum test results. Two tailed statistical significance is denoted ***/ ***, ** / ** and * / * at the 1 %, 5 % and 10 % level for the t-test and the Wilcoxon rank sum test.

Table 2:	Panel A (all bonds)			Panel B (public bonds)			Panel C (private bonds)		
Issuer Countries	Freq.	%	% cum.	Freq.	%	% cum.	Freq.	%	% cum.
United Kingdom	105	32.31	32.31	52	27.66	27.66	53	38.69	38.69
France	56	17.23	49.54	31	16.49	44.15	25	18.25	56.94
Ireland	35	10.77	60.31	27	14.36	58.51	8	5.84	62.78
Norway	27	8.31	68.62	23	12.23	70.74	4	2.92	65.70
Luxembourg	17	5.23	73.85	4	2.13	72.87	13	9.49	75.19
Netherlands	14	4.31	78.16	8	4.26	77.13	6	4.38	79.57
Monaco	13	4.00	82.16	5	2.66	79.79	8	5.84	85.41
Sweden	13	4.00	86.16	12	6.38	86.17	1	0.73	86.14
Belgium	7	2.15	88.31	5	2.66	88.83	2	1.46	87.60
Switzerland	7	2.15	90.46	7	3.72	92.55	0	0.00	87.60
Cyprus	6	1.85	92.31	3	1.60	94.15	3	2.19	89.79
Finland	5	1.54	93.85	1	0.53	94.68	4	2.92	92.71
Italy	5	1.54	95.39	2	1.06	95.74	3	2.19	94.90
Czech Republic	3	0.92	96.31	1	0.53	96.27	2	1.46	96.36
Denmark	3	0.92	97.23	1	0.53	96.80	2	1.45	97.81
Germany	3	0.92	98.15	3	1.60	98.40	0	0.00	97.81
Spain	3	0.92	99.07	0	0.00	98.40	3	2.19	100.00
Greece	2	0.62	99.69	2	1.06	99.46	0	0.00	100.00
Portugal	1	0.31	100.00	1	0.54	100.00	0	0.00	100.00
Total	**325**	**100.00**		**188**	**100.00**		**137**	**100.00**	

Table 2: Bond issues by firm domicile. All bond issues in Panel A, public placement bonds (PUBs) in Panel B and private placement bonds (PPBs) in Panel C.

Table 3:	Panel A (all firms)			Panel B (firms issuing PUBs)			Panel C (firms issuing PPBs)		
Stock Exchanges	Freq.	%	% cum.	Freq.	%	% cum.	Freq.	%	% cum.
London Stock Exchange	74	22.77	22.77	40	21.28	21.28	34	24.82	24.82
New York Stock Exchange	64	19.69	42.46	46	24.47	45.75	18	13.14	37.96
Euronext Paris	56	17.23	59.69	31	16.49	62.24	25	18.25	56.21
Oslo Stock Exchange	27	8.31	68.00	23	12.23	74.47	4	2.92	59.13
Nasdaq Stock Market	21	6.46	74.46	6	3.19	77.66	15	10.95	70.08
Pink Sheets LLC	18	5.54	80.00	6	3.19	80.85	12	8.76	78.84
Stockholm Stock Exchange	11	3.38	83.38	10	5.32	86.17	1	0.73	79.57
Euronext Amsterdam	9	2.77	86.15	6	3.19	89.36	3	2.19	81.76
Brussels Stock Exchange	7	2.15	88.30	5	2.68	92.04	2	1.46	83.22
London AIM	7	2.15	90.45	2	1.06	93.10	5	3.65	86.87
Helsinki Stock Exchange	5	1.54	91.99	1	0.53	93.63	4	2.92	89.79
Borsa Italiana	5	1.54	93.53	2	1.06	94.69	3	2.19	91.98
German Stock Exchange	4	1.24	94.77	4	2.13	96.82	0	0.00	91.98
Borsas Mercados Espanoles	3	0.92	95.69	0	0.00	96.82	3	2.19	94.17
Copenhagen Stock Exchange	3	0.92	96.61	1	0.53	97.35	2	1.46	95.63
Stock Exchange Prague	3	0.92	97.53	1	0.53	97.88	2	1.46	97.09
Bourse de Luxembourg	3	0.92	98.45	0	0.00	97.88	3	2.19	99.28
Toronto Stock Exchange	2	0.62	99.07	1	0.53	98.41	1	0.72	100.00
Euronext Lisboa	1	0.31	99.38	1	0.53	98.94	0	0.00	100.00
German Stock Exchange XETRA	1	0.31	99.69	1	0.53	99.47	0	0.00	100.00
BATS "Chi-X Europe"	1	0.31	100.00	1	0.53	100.00	0	0.00	100.00
Total	**325**	**100.00**		**188**	**100.00**		**137**	**100.00**	

Table 3: Main stock exchange listing of issuing firms. All bond issues are shown in Panel A, main listing of firms issuing public placement bonds (PUBs) in Panel B and main listing of firms issuing private placement bonds (PPBs) in Panel C.

Table 4: Bond Issues per Offering Year and Industry

Offering Year	All Bonds	Private Placement Bonds (PPB)	Public Placement Bonds (PUB)	Total		Consumer Discr.		Consumer Staples		Energy		Healthcare		Industrials		Information Technology		Materials		Tele-communi-cations		Utilities	
				PPB cum. %	PUB cum. %	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB	PPB	PUB
2002	12	2	10	1.46	5.32	0	0	0	2	1	2	0	0	0	2	0	0	1	0	0	0	0	0
2003	18	8	10	7.30	10.64	2	1	1	0	0	2	0	0	1	1	0	0	3	1	1	2	0	2
2004	10	3	7	9.49	14.36	0	0	0	0	1	0	0	1	1	2	0	0	1	2	0	2	0	2
2005	16	3	13	11.68	21.28	0	0	0	1	0	3	2	2	1	1	0	0	0	1	0	2	0	2
2006	17	5	12	15.33	27.66	0	0	1	1	1	7	0	0	1	2	0	0	2	1	0	0	0	0
2007	12	4	8	18.25	31.91	1	0	2	1	0	2	0	1	1	2	0	0	0	0	0	0	0	0
2008	19	8	11	24.09	37.77	4	2	1	1	0	3	0	0	0	3	0	0	3	1	0	1	0	1
2009	24	5	19	27.74	47.87	0	0	0	2	1	5	0	2	1	3	0	1	1	1	0	2	2	2
2010	24	12	12	36.50	54.26	1	0	2	2	3	5	2	1	1	0	1	0	1	0	0	3	1	3
2011	33	13	20	45.99	64.89	0	1	3	1	5	7	1	4	2	4	1	0	1	1	0	0	0	0
2012	30	17	13	58.39	71.81	3	1	4	1	1	2	2	3	4	1	0	1	0	1	0	0	3	0
2013	48	28	20	78.83	82.45	3	1	1	1	6	5	2	4	3	2	2	2	5	1	4	2	1	2
2014	35	17	18	91.24	92.02	1	0	0	1	8	6	1	3	3	3	0	0	1	2	2	1	1	1
2015	27	12	15	100.00	100.00	1	1	0	0	0	3	3	4	2	3	1	0	1	2	3	2	1	2
Total abs.	**325**	**137**	**188**			**16**	**7**	**15**	**14**	**27**	**52**	**13**	**25**	**21**	**29**	**5**	**4**	**20**	**14**	**10**	**17**	**9**	**17**
Total in %	**100**	**42.15**	**57.85**			**11.68**	**3.72**	**10.95**	**7.45**	**19.71**	**27.66**	**9.49**	**13.30**	**15.33**	**15.43**	**3.65**	**2.13**	**14.60**	**7.45**	**7.30**	**9.04**	**6.57**	**9.04**

Table 4 provides frequency information by offering year and industry. The total number of bond issues per placement channel (private vs. public) together with their relative share in % is given in the second last and the last line of the table. Totals in % per Industry indicate the number of placements per channel relative to the total number of issues per channel over the entire sample period. For example, 16 PPBs of firms from the consumer discretionnary industry represent 11.68 % (16/137) of all PPBs issued from 2002 through 2015.

Table 5: Cumulative Average Abnormal Returns of Firms Issuing Private (PPB) and Public Placements Bonds (PUB)

This table presents cumulative average abnormal returns (CAAR) of 137 firms issuing private placement bonds (PPB) and 181 firms issuing public placement bonds (PUB) estimating normal returns with the the market model (panels A and B) and the constant mean return model (panels C and D). The S&P500 equal weighted index is used to estimate normal returns for the market model and an estimation window of -249;-11 trading days around the event date is applied. Model parameters are estimated using ordinary least squares regressions (OLS). A time-series (ts) and a cross-sectional t-test (cs) togther with the standardized residual test of Patell (1976) (PAT), the parametric standardized creoss sectional test of Boehmer et al. (1991) (BMP), the non-parametric standardized cross-setional test of Kolari and Pynnonen (2011) (KP), the non-parametric rank test by Corrado (1985) (COR) and the generalized sign test by Cowan (1992) (COW) are used to measure statistical significance of the average cumulative abnormal returns (CAAR). The t-test for the difference in the CAAR of PPBs and PUBs is indicated in the last column. To account for non-sychronous trading, the market model is also calculated following Scholes and Williams (1977). The results do not change in any material way.

MM	Panel A: Private Placement Bonds (PPB)									Panel B: Public Placement Bonds (PUB)									
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-1.06**	57 : 71	-1.51	-1.75	-1.37	-1.53	-1.44	-0.99	-2.21	**0.41**	87 : 94	0.61	0.57	-0.59	-0.62	-0.61	0.00	-1.68	-1.56
(-10...1)	**-1.42**	44 : 84	-1.93	-2.25	-1.79	-2.00	-1.89	-1.38	-4.52	**0.23**	78 : 103	0.32	0.31	-0.80	-0.84	-0.83	-0.10	-3.02	-1.70
(-10...2)	**-1.34**	51 : 77	-1.75	-2.13	-1.52	-1.73	-1.63	-1.08	-3.28	**0.12**	78 : 103	0.16	0.17	-1.08	-1.12	-1.10	-0.42	-3.02	-1.54
(-10...8)	**-1.38**	53 : 75	-1.49	-1.84	-1.43	-1.70	-1.60	-0.96	-2.92	**-0.42**	84 : 97	-0.48	-0.53	-1.55	-1.62	-1.60	-0.66	-2.13	-0.88
(-10...10)	**-1.99**	51 : 77	-2.05	-2.50	-1.88	-2.24	-2.11	-1.61	-3.28	**2.20**	88 : 93	1.38	1.26	-0.37	-0.38	-0.37	-0.21	-1.53	-2.19
(-10...15)	**-3.29**	43 : 85	-3.04	-3.53	-2.87	-3.37	-3.18	-2.40	-4.70	**-0.41**	89 : 92	-0.44	-0.49	-1.57	-1.66	-1.63	-0.63	-1.38	-2.31
(-10...20)	**-3.49**	45 : 83	-2.96	-3.35	-2.80	-3.30	-3.11	-2.14	-4.34	**-0.08**	88 : 93	-0.08	-0.10	-1.13	-1.20	-1.19	-0.23	-1.53	-2.62
(-10...25)	**-3.72**	48 : 80	-2.93	-3.29	-2.95	-3.31	-3.12	-2.12	-3.81	**-0.09**	90 : 91	-0.08	-0.09	-0.93	-1.03	-1.01	-0.17	-1.23	-2.46
(-10...30)	**-5.33**	48 : 80	-3.93	-3.96	-3.81	-3.74	-3.52	-2.47	-3.81	**-0.19**	92 : 89	-0.16	-0.20	-1.18	-1.30	-1.29	-0.37	-0.93	-3.14
(-10...35)	**-4.79**	47 : 81	-3.33	-3.26	-3.36	-3.16	-2.98	-2.07	-3.99	**0.02**	94 : 87	0.02	0.02	-1.12	-1.19	-1.18	-0.53	-0.63	-2.52
(-10...40)	**-4.89**	49 : 79	-3.23	-3.28	-3.21	-3.24	-3.06	-1.87	-3.63	**0.97**	93 : 88	0.70	0.74	-0.71	-0.73	-0.72	-0.22	-0.78	-2.95
(-10...50)	**-5.30**	45 : 83	-3.20	-3.31	-3.15	-3.16	-2.98	-1.72	-4.34	**1.73**	94 : 87	1.18	1.15	-0.69	-0.73	-0.72	-0.35	-0.63	-3.20

CMRM	Panel C: Private Placement Bonds (PPB)									Panel D: Public Placement Bonds (PUB)									
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-1.13**	64 : 73	-1.54	-1.67	-1.48	-1.69	-1.59	-0.83	-2.15	**1.03**	98 : 90	1.55	1.20	-0.16	-0.17	-0.16	0.01	-0.85	-1.97
(-10...1)	**-1.58**	56 : 81	-2.06	-2.25	-1.92	-2.19	-2.06	-1.37	-3.52	**0.92**	97 : 91	1.33	1.09	-0.48	-0.51	-0.50	-0.10	-1.00	-2.27
(-10...2)	**-1.33**	59 : 78	-1.67	-1.91	-1.47	-1.73	-1.62	-0.74	-3.01	**0.78**	89 : 99	1.08	0.90	-0.83	-0.84	-0.83	-0.40	-2.17	-1.90
(-10...8)	**-1.78**	62 : 75	-1.85	-2.15	-1.77	-2.19	-2.06	-1.22	-2.49	**0.30**	99 : 89	0.35	0.33	-1.16	-1.21	-1.19	-0.59	-0.70	-1.68
(-10...10)	**-2.45**	63 : 74	-2.42	-2.78	-2.22	-2.69	-2.53	-1.87	-2.32	**0.45**	105 : 83	0.49	0.48	-1.05	-1.10	-1.08	-0.58	0.18	-2.26
(-10...15)	**-3.72**	56 : 81	-3.30	-3.64	-3.03	-3.62	-3.40	-2.66	-3.52	**0.38**	105 : 83	0.37	0.34	-1.19	-1.23	-1.21	-0.68	0.18	-2.68
(-10...20)	**-3.96**	59 : 78	-3.22	-3.45	-2.94	-3.43	-3.23	-2.38	-3.01	**0.45**	103 : 85	0.40	0.43	-1.08	-1.14	-1.13	-0.69	-0.12	-2.84
(-10...25)	**-4.33**	59 : 78	-3.27	-3.51	-3.16	-3.59	-3.38	-2.38	-3.01	**0.57**	104 : 84	0.47	0.51	-1.08	-1.13	-1.11	-0.63	0.03	-2.94
(-10...30)	**-5.94**	54 : 83	-4.20	-4.04	-4.04	-4.09	-3.85	-2.66	-3.87	**0.82**	104 : 84	0.64	0.64	-1.08	-1.11	-1.09	-0.67	0.03	-3.47
(-10...35)	**-5.54**	59 : 78	-3.69	-3.44	-3.79	-3.66	-3.44	-2.46	-3.01	**1.88**	108 : 80	1.37	1.30	-0.68	-0.68	-0.67	-0.44	0.62	-3.42
(-10...40)	**-5.31**	60 : 77	-3.36	-3.27	-3.42	-3.57	-3.35	-2.09	-2.83	**2.53**	103 : 85	1.76	1.53	-0.84	-0.82	-0.81	-0.51	-0.12	-3.38
(-10...50)	**-5.99**	62 : 75	-3.47	-3.34	-3.56	-3.58	-3.37	-2.12	-2.49	**3.00**	103 : 85	1.91	1.55	-0.67	-0.63	-0.63	-0.38	-0.12	-3.40

Table 6: CAAR of Firms Issuing Private (PPB) and Public Placements Bonds (PUB) with high covenant intensity

This table presents cumulative average abnormal returns (CAAR) of 84 firms issuing private placement bonds (PPB) and 94 firms issuing public placement bonds (PUB) estimating normal returns with the the market model (panels A and B) and the constant mean return model (panels C and D). The S&P500 equal weighted index is used to estimate normal returns for the market model and an estimation window of -249;-11 trading days around the event date is applied. Model parameters are estimated using ordinary least squares regressions (OLS). A time-series (ts) and a cross-sectional t-test (cs) togther with the standardized residual test of Patell (1976) (PAT), the parametric standardized creoss sectional test of Boehmer et al. (1991) (BMP), the non-parametric standardized cross-setional test of Kolari and Pynnonen (2011) (KP), the non-parametric rank test by Corrado (1985) (COR) and the generalized sign test by Cowan (1992) (COW) are used to measure statistical significance of the average cumulative abnormal returns (CAAR). The t-test for the difference in the CAAR of PPBs and PUBs is indicated in the last column. To account for non-sychronous trading, the market model is also calculated following Scholes and Williams (1977). The results do not change in any material way.

MM	Panel A: Private Placement Bonds (PPB)									Panel B: Public Placement Bonds (PUB)										
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-0.64**	41:43	-0.74	-0.95	-0.90	-1.09	-1.06	-0.86	-0.87	**0.50**	47:47	0.56	0.63	-0.30	-0.30	-0.29	0.24	-0.77	-1.10
(-10...1)	**-0.97**	30:54	-1.06	-1.39	-1.21	-1.51	-1.46	-1.21	-3.28	**0.42**	45:49	0.44	0.53	-0.24	-0.23	-0.23	0.41	-1.18	-1.32
(-10...2)	**-1.25**	33:51	-1.32	-1.75	-1.44	-1.82	-1.76	-1.46	-2.62	**0.29**	45:49	0.29	0.35	-0.44	-0.45	-0.45	-0.04	-1.18	-1.41
(-10...8)	**-1.52**	36:48	-1.32	-1.65	-1.42	-1.74	-1.68	-1.49	-1.97	**-0.93**	46:48	-0.78	-0.84	-1.14	-1.13	-1.12	-0.58	-0.98	-0.41
(-10...10)	**-2.35**	31:53	-1.95	-2.37	-1.84	-2.26	-2.19	-2.11	-3.06	**-0.79**	47:47	-0.63	-0.71	-1.03	-1.07	-1.06	-0.58	-0.77	-1.04
(-10...15)	**-3.58**	26:58	-2.66	-3.28	-2.46	-3.15	-3.05	-2.71	-4.15	**-0.43**	48:46	-0.31	-0.31	-0.53	-0.56	-0.56	-0.14	-0.56	-1.78
(-10...20)	**-3.72**	28:56	-2.53	-3.04	-2.23	-2.91	-2.82	-2.49	-3.72	**-0.41**	47:47	-0.27	-0.30	-0.56	-0.60	-0.60	-0.21	-0.77	-1.82
(-10...25)	**-4.27**	31:53	-2.70	-3.09	-2.54	-3.01	-2.91	-2.65	-3.06	**-0.96**	46:48	-0.59	-0.69	-1.03	-1.10	-1.10	-0.71	-0.98	-1.69
(-10...30)	**-5.41**	31:53	-3.20	-3.46	-2.80	-3.11	-3.01	-2.80	-3.06	**-1.02**	49:45	-0.58	-0.70	-1.16	-1.21	-1.21	-0.97	-0.36	-2.05
(-10...35)	**-4.48**	30:54	-2.50	-2.78	-2.21	-2.39	-2.31	-2.41	-3.28	**0.53**	51:43	0.29	0.32	-0.40	-0.43	-0.43	-0.38	0.06	-2.16
(-10...40)	**-4.66**	31:53	-2.47	-2.81	-2.20	-2.44	-2.37	-2.13	-3.06	**1.09**	51:43	0.56	0.60	-0.45	-0.50	-0.50	-0.44	0.06	-2.34
(-10...50)	**-4.83**	29:55	-2.34	-2.71	-1.86	-2.24	-2.16	-1.61	-3.50	**1.11**	48:46	0.52	0.55	-0.28	-0.30	-0.30	-0.30	-0.56	-2.20

CMRM	Panel C: Private Placement Bonds (PPB)									Panel D: Public Placement Bonds (PUB)									
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-0.87**	46:44	-0.97	-1.14	-1.24	-1.51	-1.46	-0.66	-0.79	**0.43**	51:47	0.47	0.48	-0.33	-0.33	-0.32	-0.02	-0.74	-1.10
(-10...1)	**-1.32**	40:50	-1.40	-1.68	-1.59	-2.01	-1.94	-1.15	-2.06	**0.54**	55:43	0.55	0.59	-0.33	-0.32	-0.32	0.22	0.07	-1.54
(-10...2)	**-1.56**	38:52	-1.59	-1.94	-1.78	-2.32	-2.24	-1.25	-2.49	**0.42**	51:47	0.41	0.44	-0.51	-0.51	-0.51	-0.11	-0.74	-1.58
(-10...8)	**-2.38**	41:49	-2.01	-2.27	-2.05	-2.56	-2.48	-1.75	-1.85	**-0.62**	54:44	-0.51	-0.55	-0.69	-0.72	-0.72	-0.20	-0.13	-1.14
(-10...10)	**-3.31**	40:50	-2.66	-2.93	-2.47	-3.08	-2.98	-2.41	-2.06	**-0.17**	56:42	-0.13	-0.13	-0.38	-0.41	-0.40	-0.06	0.28	-1.82
(-10...15)	**-4.56**	35:55	-3.28	-3.69	-2.96	-3.81	-3.68	-3.05	-3.12	**-0.43**	54:44	-0.30	-0.29	-0.69	-0.70	-0.70	-0.27	-0.13	-2.13
(-10...20)	**-4.78**	37:53	-3.15	-3.47	-2.71	-3.53	-3.41	-2.85	-2.70	**-0.44**	53:45	-0.28	-0.31	-0.86	-0.89	-0.88	-0.42	-0.33	-2.20
(-10...25)	**-5.51**	37:53	-3.37	-3.60	-3.12	-3.67	-3.54	-3.03	-2.70	**-0.63**	52:46	-0.38	-0.43	-1.03	-1.08	-1.07	-0.79	-0.54	-2.30
(-10...30)	**-6.63**	35:55	-3.80	-3.79	-3.48	-3.84	-3.71	-3.16	-3.12	**-0.54**	53:45	-0.30	-0.34	-1.09	-1.15	-1.14	-0.86	-0.33	-2.59
(-10...35)	**-5.73**	38:52	-3.11	-3.11	-3.02	-3.21	-3.10	-2.85	-2.49	**1.29**	58:40	0.68	0.73	-0.27	-0.29	-0.29	-0.21	0.68	-2.75
(-10...40)	**-5.66**	40:50	-2.91	-2.96	-2.88	-3.13	-3.02	-2.45	-2.06	**1.66**	57:41	0.83	0.86	-0.49	-0.50	-0.50	-0.19	0.48	-2.69
(-10...50)	**-6.39**	43:47	-3.00	-3.01	-2.82	-3.15	-3.05	-2.20	-1.43	**1.85**	56:42	0.85	0.82	-0.36	-0.36	-0.36	-0.08	0.28	-2.65

Table 7: CAAR of Firms Issuing Private (PPB) and Public Placements Bonds (PUB) with limit of indebtedness covenants

This table presents cumulative average abnormal returns (CAAR) of 58 firms issuing private placement bonds (PPB) and 34 firms issuing public placement bonds (PUB) estimating normal returns with the the market model (panels A and B) and the constant mean return model (panels C and D). The S&P500 equal weighted index is used to estimate normal returns for the market model and an estimation window of -249;-11 trading days around the event date is applied. Model parameters are estimated using ordinary least squares regressions (OLS). A time-series (ts) and a cross-sectional t-test (cs) togther with the standardized residual test of Patell (1976) (PAT), the parametric standardized creoss sectional test of Boehmer et al. (1991) (BMP), the non-parametric standardized cross-setional test of Kolari and Pynnonen (2011) (KP), the non-parametric rank test by Corrado (1985) (COR) and the generalized sign test by Cowan (1992) (COW) are used to measure statistical significance of the average cumulative abnormal returns (CAAR). The t-test for the difference in the CAAR of PPBs and PUBs is indicated in the last column. To account for non-sychronous trading, the market model is also calculated following Scholes and Williams (1977). The results do not change in any material way.

MM	Panel A: Private Placement Bonds (PPB)									Panel B: Public Placement Bonds (PUB)									
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-0.62**	24:30	-0.50	-0.63	-0.79	-0.97	-0.87	-0.58	-1.26	**2.30**	17:12	1.01	1.71	1.12	1.30	1.16	0.87	0.47	-1.76
(-10...1)	**-1.16**	17:37	-0.90	-1.17	-1.14	-1.43	-1.29	-0.98	-3.17	**2.73**	17:12	1.15	2.01	1.32	1.47	1.32	1.05	0.47	-2.31
(-10...2)	**-1.42**	19:35	-1.07	-1.43	-1.30	-1.67	-1.51	-1.05	-2.63	**1.86**	18:11	0.75	1.31	0.94	1.09	0.98	0.55	0.84	-1.89
(-10...8)	**-2.26**	21:33	-1.40	-1.74	-1.61	-1.90	-1.72	-1.31	-2.08	**-0.85**	19:10	-0.28	-0.33	0.29	0.32	0.29	-0.05	1.21	-0.49
(-10...10)	**-3.34**	19:35	-1.97	-2.43	-2.01	-2.39	-2.16	-1.95	-2.63	**-0.33**	18:11	-0.11	-0.12	0.41	0.44	0.39	0.08	0.84	-0.95
(-10...15)	**-4.99**	16:38	-2.65	-3.32	-2.52	-3.12	-2.82	-2.60	-3.44	**-0.26**	19:10	-0.08	-0.06	0.69	0.59	0.53	0.41	1.21	-1.03
(-10...20)	**-5.61**	16:38	-2.72	-3.37	-2.48	-3.14	-2.84	-2.52	-3.44	**-0.05**	19:10	-0.01	0.02	0.60	0.62	0.56	0.57	1.21	-1.86
(-10...25)	**-5.50**	20:34	-2.48	-2.88	-2.30	-2.65	-2.40	-2.19	-2.35	**-0.70**	17:12	-0.17	-0.16	0.28	0.29	0.26	0.04	0.47	-1.02
(-10...30)	**-6.77**	19:35	-2.86	-3.10	-2.44	-2.69	-2.44	-2.43	-2.63	**-0.28**	17:12	-0.06	-0.04	0.12	0.11	0.10	0.06	0.47	-0.84
(-10...35)	**-5.67**	19:35	-2.26	-2.55	-1.94	-2.16	-1.96	-2.16	-2.63	**4.36**	20:09	0.94	1.12	0.99	1.03	0.93	0.52	1.58	-2.24
(-10...40)	**-5.42**	20:34	-2.05	-2.33	-1.78	-2.06	-1.87	-1.74	-2.35	**6.19**	20:09	1.26	1.43	1.25	1.32	1.18	0.45	1.58	-2.36
(-10...50)	**-5.96**	17:37	-2.06	-2.36	-1.61	-1.92	-1.73	-1.48	-3.17	**7.31**	19:10	1.36	1.51	1.62	1.60	1.43	0.54	1.21	-2.43

CMRM	Panel C: Private Placement Bonds (PPB)									Panel D: Public Placement Bonds (PUB)									
(t,t)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	CAAR in %	Pos:Neg	t-test (ts)	t-test (cs)	PAT (1976)	BMP (1991)	KP (2010)	COR (1985)	COW (1992)	Delta CAAR t-test
(-10...0)	**-0.62**	30:28	-0.49	-0.59	-0.79	-1.00	-0.90	-0.03	-0.49	**2.14**	22:12	1.03	1.27	0.79	0.95	0.84	0.52	0.42	-1.39
(-10...1)	**-1.42**	24:34	-1.09	-1.29	-1.27	-1.61	-1.44	-0.61	-2.07	**2.57**	21:13	1.18	1.45	0.85	0.99	0.87	0.57	0.07	-1.92
(-10...2)	**-1.56**	25:33	-1.15	-1.40	-1.37	-1.79	-1.61	-0.56	-1.81	**2.17**	20:14	0.96	1.07	0.72	0.81	0.72	0.37	-0.28	-1.62
(-10...8)	**-3.49**	24:34	-2.13	-2.42	-2.24	-2.80	-2.52	-1.62	-2.07	**-0.86**	22:12	-0.31	-0.32	-0.01	-0.02	-0.02	-0.33	0.42	-0.86
(-10...10)	**-4.84**	24:34	-2.80	-3.14	-2.73	-3.35	-3.01	-2.41	-2.07	**-0.18**	23:11	-0.06	-0.07	0.19	0.20	0.18	-0.09	0.77	-1.50
(-10...15)	**-6.58**	22:36	-3.43	-3.86	-3.14	-4.00	-3.60	-3.05	-2.60	**-1.26**	24:10	-0.39	-0.31	-0.02	-0.02	-0.02	-0.22	1.13	-1.22
(-10...20)	**-7.25**	20:38	-3.46	-3.87	-3.06	-3.90	-3.50	-2.95	-3.13	**-1.17**	21:13	-0.33	-0.32	-0.11	-0.13	-0.12	-0.09	0.07	-1.47
(-10...25)	**-7.27**	22:36	-3.22	-3.45	-2.88	-3.34	-3.00	-2.51	-2.60	**-1.70**	21:13	-0.45	-0.49	-0.29	-0.34	-0.30	-0.50	0.07	-1.37
(-10...30)	**-8.38**	20:38	-3.48	-3.45	-2.98	-3.29	-2.96	-2.61	-3.13	**-1.12**	21:13	-0.28	-0.28	-0.49	-0.51	-0.45	-0.47	0.07	-1.55
(-10...35)	**-7.13**	22:36	-2.79	-2.85	-2.49	-2.76	-2.48	-2.36	-2.60	**4.15**	23:11	0.97	0.96	0.46	0.55	0.48	0.24	0.77	-2.26
(-10...40)	**-6.70**	22:36	-2.49	-2.54	-2.27	-2.62	-2.35	-1.87	-2.60	**5.89**	23:11	1.31	1.25	0.72	0.83	0.74	0.28	0.77	-2.33
(-10...50)	**-8.17**	25:33	-2.78	-2.70	-2.41	-2.60	-2.33	-1.86	-1.81	**7.57**	22:12	1.54	1.42	1.20	1.29	1.14	0.63	0.42	-2.57

Table 8: The U-Shape between CAAR and Covenant Intensity

CAAR -10;30	(1) PPBs	(2) PPB sample split below turning point	(3) PPB sample split above turning point	(4) PPB sample split below mean	(5) PPB sample split above mean
covscore_adj	0.0523***	0.0166	-0.0210***	0.0132	-0.0262***
	(0.0118)	(0.0131)	(0.00778)	(0.0109)	(0.00763)
covscore_adj_2	-0.00361***				
	(0.000810)				
Constant	0.155	0.409**	0.409***	0.261*	0.269**
	(0.116)	(0.173)	(0.0945)	(0.132)	(0.127)
Industry fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	128	44	84	52	76
Adjusted R-squared	0.285	0.176	0.231	0.235	0.301

This table reports the results parts of the test of the U-shaped relationship between CAAR and Covenant Intensity. Heteroskedasticity-robust standard errors are in parenthesis. The data consists of public and private placement primary market bond issues over the period January 2002 to December 2015. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Lind and Mehlum (2010) test of U-shape:

Specification: f(x)=x^2, Extreme point: 7.251552
Test: H1: Inverse U shape; vs. H0: Monotone or U shape

	Lower bound	Upper bound
Interval	0	15
Slope	0.0522848	-0.0558675
t-value	4.429185	-4.225583
P>t	.0000117	.0000256

Overall test of presence of a Inverse U shape: t-value = 4.23
P>t = .0000256
90% Fieller interval for extreme point: [6.5451562; 8.0230662]

Table 9: Other Explanations for Abnormal Returns for Firms issuing PPBs

CAAR -10;30	(1) Inverted U Baseline	(2) Credit Risk	(3) Market liquidity	(4) Market conditions	(5) Other controls	(6) Full model	(7) Restricted model	(8) Factor model [covscore variables replaced by factors]
placement	-0.189***	-0.158***	-0.158***	-0.197***	-0.192**	-0.192***	-0.157***	-0.090***
	(0.070)	(0.057)	(0.057)	(0.070)	(0.077)	(0.061)	(0.052)	(0.029)
Covscore	-0.0163	-0.0016	-0.0016	-0.0207	-0.0007	-0.0002		-0.0129
[f1_mc in col.8]	(0.014)	(0.012)	(0.012)	(0.014)	(0.013)	(0.012)		(0.013)
covscore2	0.0005	-0.0004	-0.0004	0.0009	-0.0007	-0.0005		-0.0163
[f2_loi in col. 8]	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.024)
covscoreXplacement	0.0480**	0.0371**	0.0371**	0.0470**	0.0362*	0.0334*	0.0320**	0.0413**
[f1Xplacement in col.8]	(0.019)	(0.017)	(0.017)	(0.019)	(0.020)	(0.017)	(0.014)	(0.021)
covscore2Xplacement	-0.0029**	-0.0022*	-0.0022*	-0.0028**	-0.0021	-0.0020	-0.0023**	-0.0037
[f2Xplacement in col.8]	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.024)
rating		0.002				0.002	0.003	0.003
		(0.004)				(0.006)	(0.006)	(0.006)
leverage		0.090				0.000	-0.009	-0.017
		(0.093)				(0.089)	(0.089)	(0.090)
bmf			0.002			0.128	0.114*	0.130*
			(0.004)			(0.076)	(0.076)	(0.077)
emi			0.090			0.049	0.049	0.043
			(0.093)			(0.137)	(0.138)	(0.138)
gdp360						-0.008	-0.004	-0.003
						(0.023)	(0.022)	(0.023)
benchmark				0.000		0.014	0.012	0.016
				(0.021)		(0.017)	(0.017)	(0.018)
slope				0.016		-0.027	-0.022	-0.022
				(0.013)		(0.034)	(0.034)	(0.034)
vix				-0.025*		0.006**	0.005**	0.006**
				(0.031)		(0.002)	(0.002)	(0.002)
mscii180				0.003*		-0.001*	-0.001*	-0.002**
				(0.002)		(0.001)	(0.001)	(0.001)
size					-0.006	0.012	0.013	0.007
					(0.013)	(0.011)	(0.011)	(0.019)
maturity					0.001	-0.001	-0.001	-0.008
					(0.002)	(0.002)	(0.002)	(0.009)
top_tier					-0.006	-0.027	-0.026	-0.023
					(0.024)	(0.021)	(0.021)	(0.024)
age					-0.014	-0.042	-0.037	0.050
					(0.028)	(0.028)	(0.026)	(0.027)
call					0.050**	0.044**	0.041**	0.050**
					(0.022)	(0.021)	(0.021)	(0.022)
ref					-0.002	0.010	0.008	0.007
					(0.020)	(0.019)	(0.020)	(0.019)
mtb					-0.009	-0.009	-0.005	-0.008
					(0.007)	(0.008)	(0.008)	(0.009)
exchange					0.005	-0.029	-0.020	-0.023
					(0.027)	(0.024)	(0.023)	(0.024)
s144					0.041	0.047*	0.044*	0.050*
					(0.026)	(0.026)	(0.027)	(0.027)
Constant	0.127	0.048	0.048	0.017	0.194	-0.050	-0.099	-0.140
	(0.080)	(0.085)	(0.085)	(0.117)	(0.151)	(0.191)	(0.186)	(0.190)
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	309	289	309	309	283	270	270	270
Adjusted R-squared	0.096	0.077	0.100	0.137	0.086	0.121	0.129	0.120

Table 9: This table reports the results of the cross-sectional regression of the CAAR -10;30 on a set of variables proxying for credit risk (specification 2), market liquidity (specification 3), market conditions (specification 4) and other controls (specification 5). Specification 1 is the baseline model, specification 6 the full model. Specification 7 imposes a restriction on covscore and covscore2 realated to public placements to be zero. In specification 8, covscore and covscore2 are replaced by a monitoring factor (f1_mc) and a limit of indebtedness factor (f2_loi). Heteroskedasticity-robust standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively

Table 10: Confounding Events Analysis		(A) No restrictions	(B) High cov. intensity	(C) Limit of indebtedness
Earnings Announcements	**Observations (A/B/C)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**
Operating results	123/80/49	-5.61 (-2.36)	-6.72 (-2.97)	-8.33 (-3.01)
Sales / Trading statement	122/82/51	-5.45 (-2.26)	-6.15 (-2.69)	-7.35 (-2.61)
Earnings	87/54/31	-4.69 (-2.26)	-5.55 (-2.98)	-6.71 (-2.42)
Guidance raised	126/82/52	-5.62 (-2.29)	-6.28 (-2.76)	-7.32 (-2.64)
Guidance new / confirmed	95/64/36	-5.86 (-2.79)	-6.15 (-2.95)	-7.92 (-2.84)
Guidance lowered	128/84/53	-5.60 (-2.30)	-6.22 (-2.78)	-7.42 (-2.73)
Earnings calls	96/60/35	-4.86 (-2.03)	-5.33 (-2.39)	-7.48 (-2.47)
Guidance update	126/84/53	-5.61 (-2.27)	-6.22 (-2.78)	-7.42 (-2.73)
Dividend Announcements	**Observations (A/B/C)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**
Dividend decreases	126/82/53	-5.56 (-2.52)	-6.19 (-2.70)	-7.42 (-2.73)
Dividend increases	118/79/48	-5.05 (-2.05)	-5.28 (-2.41)	-6 (-2.21)
Dividend initiation	127/845/53	-5.32 (-2.26)	-6.22 (-2.78)	-7.42 (-2.73)
Ex-Dividend date (regular)	98/68/42	-5.78 (-2.22)	-6.04 (-2.89)	-7.32 (-2.94)
Ex-Dividend date (special)	127/84/53	-5.53 (-2.26)	-6.22 (-2.78)	-7.42 (-2.73)
Special dividend announced	128/84/53	-5.60 (-2.30)	-6.22 (-2.78)	-7.42 (-2.73)
Stock dividend	128/84/53	-5.60 (-2.30)	-6.22 (-2.78)	-7.42 (-2.73)
Stock splits	128/84/53	-5.60 (-2.30)	-6.22 (-2.78)	-7.42 (-2.73)
Merger Announcements	**Observations (A/B/C)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**
M&A transation announcement	116/77/47	-5.41 (-2.31)	-6.62 (-2.88)	-8.08 (-2.85)
M&A transaction cancellation	125/83/52	-5.82 (-2.41)	-6.59 (-3.06)	-8.03 (-3.11)
M&A rumors and discussions	101/71/48	-5.71 (-2.35)	-5.8 (-2.72)	-5.88 (-2.18)
Financing Announcement	**Observations (A/B/C)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**
SEO announcement	127/84/53	-5.45 (-2.25)	-6.22 (-2.78)	-7.42 (-2.73)
Public offering of derivatives	128/84/53	-5.60 (-2.30)	-6.22 (-2.78)	-7.42 (-2.73)
Debt financing related	125/82/51	-5.79 (-2.44)	-6.10 (-2.67)	-7.27 (-2.58)
Analyst Announcement	**Observations (A/B/C)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**	**CAAR -10;30 (t)**
Positive change in recomm.	122/81/52	-5.71 (-2.26)	-6.27 (-2.70)	-7.45 (-2.68)
Negative change in recomm.	112/73/47	-4.76 (-1.95)	-4.9 (-2.35)	-5.37 (-2.29)

Table 10: Confounding Events Analysis. This table shows the cumulative average abnormal return (CAAR) from the market model after dropping PPB issues for which potentially confounding events are observed in the event window. Panels A, B and C show the CAAR after dropping such events with no restrictions, high covenant intensity and limit of indebtedness covenants attached respectively. Statistical significance is calculated under the null hypothesis that the CAAR is equal to zero applying the t-test of Brown and Warner (1980). T-values are given in parenthesis.

Table 11: Abnormal Returns and Uncertainty about Credit Risk

	(1)	(2)	(3)	(4)	(5)	(6)
CAAR -10;30	Baseline Regression	CRA dispersion	Altman's Z-score	Z-score and CRA dispersion (2)+(3)	Altman's zscore w. covenants (larger sample)	Altman's zscore w. factors (larger sample)
placement	-0.189***	-0.321**	0.0214	-0.107	-0.199**	-0.0381
	(0.0701)	(0.132)	(0.117)	(0.348)	(0.0776)	(0.0268)
covscore	-0.0163	0.0138	0.0382	0.0421	-0.0164	-0.0243
	(0.0136)	(0.0291)	(0.0236)	(0.0275)	(0.0153)	(0.0215)
covscore2	0.000547	-6.20e-05	-0.00210	-0.00261	0.000412	-0.0313*
	(0.000928)	(0.00315)	(0.00271)	(0.00302)	(0.00100)	(0.0184)
covscoreXplacement	0.0480**	0.124*	0.0493	0.0352	0.0446**	0.0432
	(0.0191)	(0.0610)	(0.0526)	(0.0673)	(0.0205)	(0.0278)
covscore2Xplacement	-0.00288**	-0.0145**	-0.00682	-0.00531	-0.00246*	0.0208
	(0.00126)	(0.00650)	(0.00595)	(0.00740)	(0.00131)	(0.0215)
analyst coverage						
analyst coverageXplacement						
consensus						
consensusXplacement						
cr_dispersion		0.00640		0.0147		
		(0.00856)		(0.0417)		
cr_dispersionXplacement		0.0250**		0.0187		
		(0.00955)		(0.0409)		
zscore			-0.0716**	-0.0690***	0.0755**	0.0874***
			(0.0261)	(0.0236)	(0.0296)	(0.0303)
zscoreXplacement			-0.00820	-0.00732	-0.00985	-0.0285
			(0.0241)	(0.0294)	(0.0386)	(0.0392)
Constant	0.127	-0.0378	-0.231**	-0.133	0.250**	0.159*
	(0.0797)	(0.0978)	(0.100)	(0.315)	(0.0987)	(0.0940)
Industry fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	309	60	47	47	256	256
Adjusted R-squared	0.131	0.213	0.585	0.546	0.185	0.160

Table 11: This table reports the results of the cross-sectional regression of the CAAR -10;30 on a set of variables. Specification (1) is the baseline regression as in Table 9, specification (1). The pattern of disagreement between the S&P and Moody's credit rating is measured by "cr_dispersion". I map the ratings as assigned by the credit rating agencies (CRAs) and as available to investors at the event date to a numerical scale, a lower number representing a higher credit rating. The difference in the numerical value between the CRAs is represented by "cr_dispersion". The data are from Bloomberg. Z-score is Altman's (1977) score, modified and calculated as in Denis & Mihov (2003). In specification 6, covscore and covscore2 are replaced by a monitoring factor and a financing factor. Heteroskedasticity-robust standard errors are in parenthesis. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

10 Figures

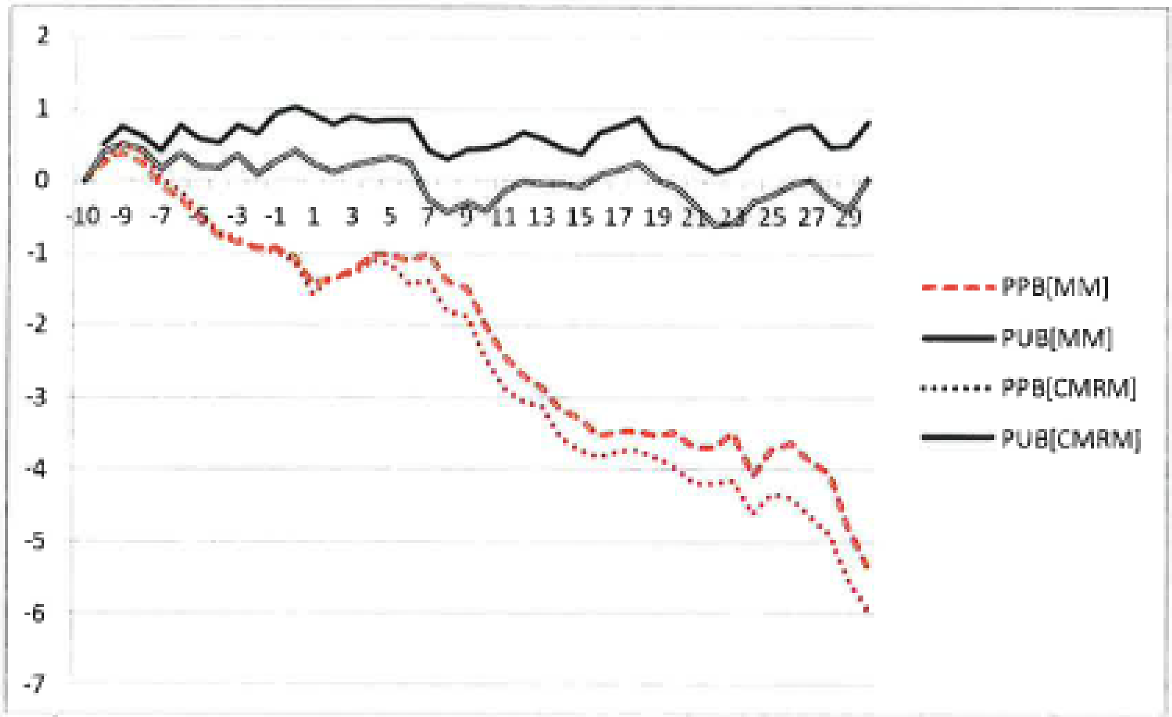

Figure 1: Plot of cumulative average abnormal returns (CAAR) for the announcement of 137 private placement bonds (PPBs) and 188 public placement bonds (PUBs) from event day -10 to event day +30. The abnormal return ist calculated using the market model and the S&P500 (equal weighted) and the constant mean return model as the normal return measure.

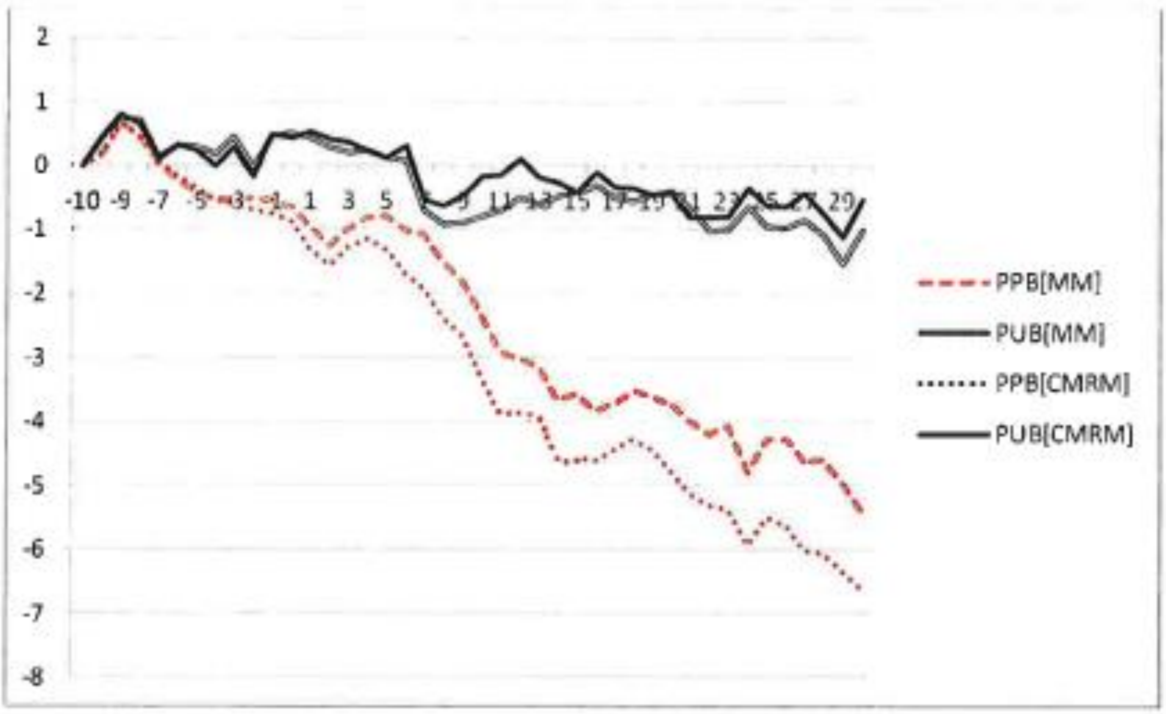

Figure 2: High covenant intensity. Plot of cumulative average abnormal returns (CAAR) for the announcement of 84 private placement bonds (PPBs) and 94 public placement bonds (PUBs) with more or equal to 8 covenants attached from event day -10 to event day +30. The abnormal return ist calculated using the market model and the S&P500 (equal weighted) and the constant mean return model as the normal return measure.

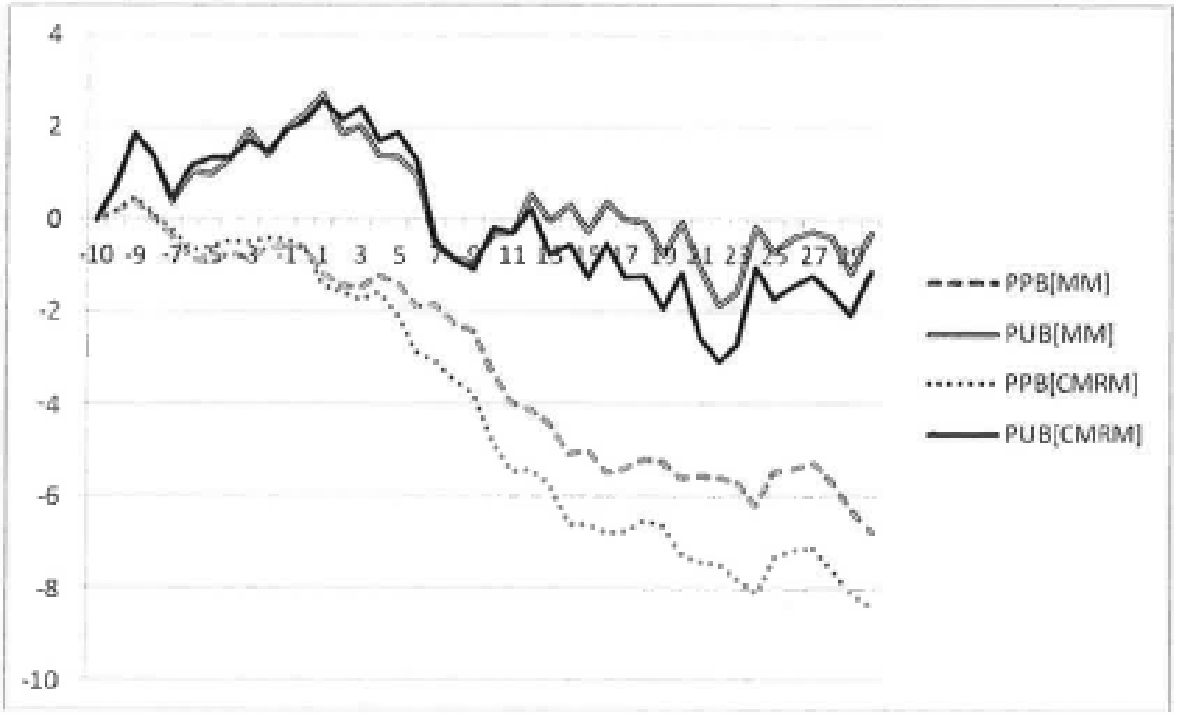

Figure 3: Plot of cumulative abnormal return for the announcement of 58 private placement bonds (PPBs) and 34 public placement bonds (PUBs) with limit of indebtedness covenants attached from event day – 10 to event day + 30. The abnormal return is calculated using the market model and the S&P500 (equal weighted) and the constant mean return model as the normal return measure.

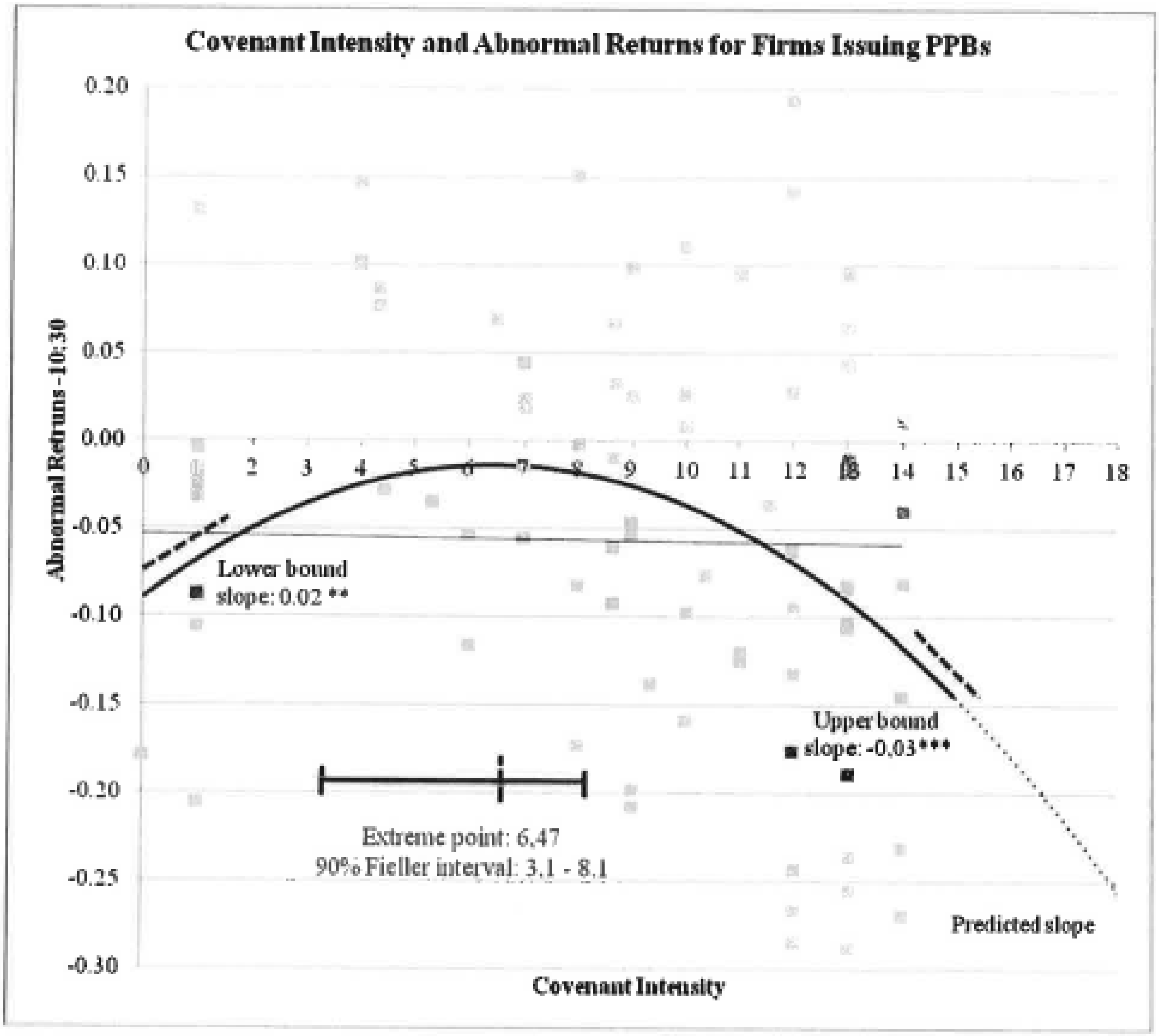

Figure 4: Plot of fitted values from a linear regression of the cumulative average abnormal return (CAAR) -10;30 on covenant score ("covscore") and covenant score squared ("covscore2") for private placement bonds (PPBs) together with results following Lind and Mehlum (2010) estimating the lower and upper bound slope, the extreme point and the Fieller interval. The dotted blue line is the out of sample estimated relationship between covenant intensity and abnormal returns. Dark grey squares are the observed abnormal returns given a specific level of covenant intensity.

11 Appendices

Appendix A Description of Debt Covenants

The following table provides an overview of all covenant variables and their Bloomberg definitions.

Variable	Covenant	Bloomberg definition
cov1	Restricted payments	Indicates a negative or restrictive covenant that limits an issuer's ability to make distributions, whether in the form of cash, assets or securities to shareholders, to redeem subordinated debt, repurchase equity or provide dividends.
cov2	Financial Statements	Indicates the existence of an affirmative or restrictive covenant requiring the borrower to deliver to lenders periodic financial statements.
cov3	Default Info available	Indicates whether covenant/default information is available.
cov4	Force Majeure	Indicates a clause that allows the underwriter to cancel the issuance of the bond should certain events occur.
cov5	Material Adverse Change Clause	Indicates a covenant or clause in the loan documentation which is triggered by an event, condition or change which materially and adversely affects, or could reasonably be expected to materially and adversely affect, a company's financial results, financial condition, business, or prospects.
cov6	Negative Pledge Clause	Indicates a covenant in the credit agreement whereby the company is prohibited from pledging or placing liens on certain assets.
cov7	Limit of Indebtedness	Indicates a negative or restrictive covenant that places limitations on the amount of debt that the issuer can incur. This can be expressed as a percentage of assets or in monetary terms.
cov8	Cross Default	Indicates a stipulation stating that if an issuer is in default on other borrowings, such non-payment is also considered default in respect to the issue with the cross default covenant.
cov9	Negative Covenant Indicator	Indicates a restrictive bond clause intended to prevent a corporation from giving benefits to the shareholders at the expense of the bondholders.
cov10	Sales of Assets Restriction	Indicates a negative or restrictive covenant that limits the ability of the issuer to sell any or all of its assets.
cov11	Restriction on Activities	Indicates a negative covenant that can apply to any restrictions on the business activities of the issuer.
cov12	Debt Service Coverage Ratio	Indicates cash available for debt service/total or senior debt service. In corporate finance, it is the amount of cash flow available to meet annual interest and principal payments on debt, including sinking fund payments.

Appendix A Description of Debt Covenants (continued)

cov13	Free Cash Flow to Debt Service	Indicates if the issuer has supplied specific ratios and has pledged to maintain these ratios throughout the life of the bond.
cov14	Restrictive Covenant Indicator	Indicates any pledge made by the issuer to refrain from an activity that will be considered detrimental to the bondholders.
cov15	Merger Restrictions Covenant Indicator	Indicates a negative or restrictive covenant placed on the issuer which states that the issuer may not merge or consolidate with any other entity without satisfying certain conditions.
cov16	Limitation on Sale and Leaseback	Indicates a restrictive or negative covenant that prevents the issuer from selling assets (or removing them from the balance sheet for accounting purposes) then leasing them back from the company to which they were sold.
cov17	Limitation on Subsidiary Debt	Indicates a negative or restrictive covenant that places limitations on the amount of debt that the issuer's subsidiaries can incur. This can be expressed a as percentage of assets or in monetary terms.
cov18	Collective Action Clause	Indicates an additional covenant clause designed to give a supermajority of bondholders (usually 66.66% or 75%) the ability to consent to changes in the fundamental terms of the bond.

Appendix B Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence

The following description of CreditmodelTM Corporates 2.6 (CM) is based on the S&P Global Market Intelligence technical note describing the short form credit scoring model (August 2016). A more comprehensive unpublished technical reference guide is available from S&P Global Market Intelligence.

Overview: [CM is] a statistical model trained on credit ratings from S&P Global Ratings. [CM] is a widely used statistical tool that facilitates [the] evaluation of a company's credit quality by generating rating scores [from aaa, with a numerical value of 1, to ccc or lower, with a numercal value of 18] for both public and private corporates globally. [It] utilizes both financial data from corporates and the most relevant macroeconomic data, to generate a quantitative rating score that statistically matches a credit rating issued by S&P Global Ratings. S&P Global Ratings does not contribute to or participate in the creation of rating scores generated by S&P Global Market Intelligence. Lowercase nomenclature is used to differentiate S&P Global Market Intelligence PD credit model scores from the credit ratings issued by S&P Global Ratings. [CM] covers both privately held and publicly listed corporates. The model's primary output is a lower-case letter grade score. [It provides users] with access to estimates of creditworthiness for more than 48,0003 non-financial corporations globally, spanning more than 10 years, based upon S&P Capital IQ's database of public and private company fundamentals.

Trained on S&P Global Ratings credit ratings and S&P Capital IQ Platform's Financial Data: [CM] uses more than 10 years of S&P Global Ratings' historical ratings for corporate companies. [CM] uses standalone credit profiles (SACP) where available, or strippes any group or parental support from the final rating if the standalone credit profile is unavailable, in order to obtain the credit profile of a company prior to any extraordinary support considerations. [CM] uses more than 52,000 observations globally [and more than 8'500 for Europe] for corporates, that [were] complemented with internal standalone assessments generated for companies operating in emerging markets to enrich [the] training dataset. [S&P] collected all relevant financial items for the same companies, from the S&P Capital IQ Platform standardized fundamentals.

Appendix B Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

Systemic Risk Data: [Context was considered when developing the] model [by considering] credit ratings by S&P Global Ratings via the Corporate Industry and Country Risk Assessment (CICRA). A CICRA is a combination of country risk and industry risk. Country risk refers to the risk associated with investing in a country. It is a broad and general term that represents risks linked to changes in the business environment that may adversely affect operating profits or the value of assets in a specific country. This type of risk affects all companies operating within a particular country and is a blend of monetary factors (e.g., currency control), political factors (e.g., civil war), and operating factors (e.g., corruption). For Country Risk, S&P Global Market Intelligence has developed a quantitative model that generates Country Risk Scores that closely align with S&P Global Ratings' assessments, and expands the coverage to 247 countries worldwide by establishing a "proxy mechanism" based on geographic proximity considerations, regional influences, independence (or not) of the central banks, the degree and evolution of a count ry's economic development and financial regulatory environment and its type of political system. Industry risk is usually determined by elements such as barrier to entry, ease of conversion, level of competition, market fragmentation, etc. This is implicitly captured in CM2.6 by training industry-specific sub-models or adding dummy variables to reflect differences in specific industry sectors.

Variable Selection Process: [CM tested] more than 100 alternative financial and non-financial items, in order to investigate the most predictive variables for modelling purposes [and] applied a vigorous, cutting-edge procedure for the variable selection process that helps to prescreen what could be included as an input for the model. In order to select the final set of inputs and variables we used both statistical analysis and business judgment to weight the following considerations: [a.] Availability of Factors: All factors included in the model must be widely available on a consistent basis over time for companies in each sector. Some factors have a high predictive power but are seldom reported by companies (e.g. some cash flow items of private corporates); while these factors may help boost a model's performance, such a model would be irrelevant for

Appendix B Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

firms that do not report similar information. [b.] Correlation: Highly correlated factors do not provide additional insights and could distort model performance. [CM] used correlation analysis to identify and remove correlated variables. [c.] Representation of All Relevant Risk Dimensions: In order to capture the variety of factors that influence the creditworthiness of corporates, [CM] referred to the list of "risk dimensions" that S&P Global Ratings uses for the analysis of corporate firms, and classified each candidate variable into its corresponding risk dimension, using expert judgement. Then, [CM] selected the variables that would comprise these risk dimensions from a range of categories, including financial information, as well as economic and industry-based risk indicators to ensure a proper balance of microeconomic and macroeconomic factors, similar to how a credit analyst would analyze a corporate company. [CM controls for] potential differences in the explanatory power of factors in different industries, where relevant [and] early warning signals such as low values of Debt / Capital. [According to the technical reference guide, p. 33, CM applies the following variables for European corporates: total assets to represent the company size effect, return on capital to reflect profitability, cash from operations interest coverage to account for debt service capability, asset turnover to reflect efficiency, debt / debt + equity to represent gearing, free operating cash flow / debt to calculate debt service capability, operating income before depreciation and amortisation to reflect profitability and long term liability / equity to again reflect gearing.]

Regional and Sector Segmentation: In order to achieve optimal model performance and stability of the results, CM2.6 was trained using a regional/sector segmentation based on similarities of available financials and rating distributions, as well as taking into account data availability and other macroeconomic considerations. Europe was trained with 10 sub-regions based on the ratings distribution [and] 19 industry sector dummy variables. Finally, the airlines industry was treated as a separate, global model due to the globalized nature of this industry. More details can be found in the technical reference guide.

Appendix B Creditmodel™ Corporates 2.6 of S&P Global Market Intelligence (continued)

Methodology Most of the models available in the market only employ simple logistic regression techniques. [The CM] model employs an advanced generalization of the logistic regressions, based on the family of Exponential Density Functions. It uses the prior distribution of all S&P Global Ratings credit ratings in the training dataset as an “anchor distribution”, and modifies it in proportion to how much the financials of a specific company deviate from those of companies used in the anchor distribution. The process of variable selection considers both linear terms and terms of higher order, and selects the final variables according to k-fold Greedy Forward Approach, a widely-used statistical method that ensures a good fit out-of-sample and out-of-time. The model uses a number of techniques, including variable t ransformations, which minimize the impact of extreme values. It also uses various constraints, which avoid risk of model over-fitting without any loss of data as well as a more accurate estimation of the parameters and final output. The model maximizes the maximum likelihood function within a Maximum Expected Utility, adapted to a multi-state case (the rating categories, on which the model is trained, are not binary, but 18 in total), and uses the Akaike Information Criterion (AIC) to limit the maximum number of variables that are included (model parsimony). This optimization process ensures the model exhibits greater stability and out-of-time performance. Monotonicity constraints are applied to ensure that the model produces outputs that follow economic intuition.

Annual Model Validation Since the release of CM2.6 in 2013, S&P Global Market Intelligence has conducted a detailed performance evaluation annually, based on the actual performance data and provided the results of the validation to users. If a significant deterioration in model performance is observed, S&P Global Market Intelligence will consider a recalibration of the parameters or a review of the risk drivers. [The CM performance is measured in percent of exact matches, +/- 1 notch, +/- 2 notches and +/- 3 notches deviation from the S&P Global Ratings. The last available validation was done in July 2016 and has resulted in 22% exact matches, 56 % matches within 1 notch, 78 % within 2 notches and 88 % within 3 notches.]

Appendix C: Confounding Events

Earnings reports / earnings announcements		
ce_ea1	Announcement of Operating Results	Announcements of quarterly, annual, or other periodic operating results.
ce_ea2	Announcements of Sales/Trading Statement	Announcements of results other than earnings results.
ce_ea3	Announcement of Earnings	Announcements of quarterly, annual, or other periodic earnings
ce_ea4	Corporate Guidance-Raised	An announcement that a company expects operating results to be higher than its previously announced expectations.
ce_ea5	Corporate Guidance-New/Confirmed	An announcement of a company's expected operating results or announcements that the company remains confident of the previously announced earnings results.
ce_ea6	Corporate Guidance-Lowered	An announcement that a company expects operating results to be lower than its previously announced expectations.
ce_ea7	Earnings Calls	This pertains to when a company conducts a "Conference Call" to discuss its quarterly, annual, or other periodic earnings.
ce_ea8	Guidance/Update Call	This pertains to when a company conducts a "Conference Call" to discuss its guidance and expectations for the future periods or to update its shareholders, analysts, and investors on its operations during a particular period.
Dividends		
ce_da1	Dividend Decreases	When a company either announces that they are going to pay a divided that is lower than was previously announced or announces that they are going to pay a lower dividend than they have paid in the past. It only includes dividends paid in cash.
ce_da2	Dividend Increases	When a company announces that they are going to pay a divided that is higher than was previously announced, announces that they are going to pay a higher dividend than they have paid in the past, or announces that they are going to begin paying a regular divided. It only includes dividends paid in cash. Declarations of non-periodic dividend payments are covered under "Special Dividend Announced."
ce_da3	Dividend Initiation	When a company announces its maiden dividend or reinitiates dividend payment after at least five (5) years without paying dividends.
ce_da4	Ex-Div date (Regular)	The first day of the ex-dividend period for a periodically recurring dividend. An investor who does not own the stock before this date is not eligible to receive the dividend.
ce_da5	Ex-Div Date (Special)	The first day of the ex-dividend period for a non-periodic dividend. An investor who does not own the stock before this date is not eligible to receive the dividend.
ce_da6	Special Dividend Announced	An announcement of a non-recurring distribution of company assets, usually in the form of cash to shareholders.
ce_da7	Stock Dividend (<5%)	A dividend payment made in the form of additional shares rather than a cash payout whose value is less than 5% of the value of the shares held. Stock dividends greater than 5% are considered "Stock Splits & Significant Stock Dividends".
ce_da8	Stock Splits & Significant Stock Dividends	When a company increases the number of outstanding shares of its stock but the proportionate equity of each shareholder remains the same.
Merger announcements		
ce_ma1	M&A (Merger & Acquisition) Transactions Announcements	The announcement of the combining of two or more entities into one through a purchase acquisition.
ce_ma2	M&A (Merger & Acquisition) Transaction Cancellation	The cancellation of an announced transaction between two or more entities seeking to combine into one through a purchase acquisition.
ce_ma3	M&A (Merger & Acquisition) Rumors and Discussions	This development pertains to rumors and confirmed announcements for potential or initial talks for a merger, acquisition, and stake sale involving company(s) before any actual agreement is signed between the target(s) and buyer(s). This development also includes denials pertaining to merger, acquisition, and sale talks amongst the concerned companies.
Seasoned equity offerings (SEOs)		
ce_fa1	Follow-on Equity Offering	An offering of additional shares of equity to the public by a company following the company's initial public offering (IPO).
ce_fa2	Derivative/Other Instrument Offerings	The public offering of commodities, bonds, equities, currencies, futures, or options by an underwriter for a company.
ce_fa3	Debt Financing Related (adjusted by bond issue which we are looking on)	Announcements that a company is raising money through private placement of debentures, bonds, notes, or mortgages or borrowing directly from financial institutions.

Appendix C: Confounding Events (continued)

ce_fa3	Debt Financing Related (adjusted by bond issue which we are looking on, including ambiguous cases)	Announcements that a company is raising money through private placement of debentures, bonds, notes, or mortgages or borrowing directly from financial institutions.
<u>Analyst recommendation</u>		**[Not part of the S&P Key Development coverage.] =CIQRANGEVN("*ISSUER*"; "IQ_AVG_BROKER_REC";IQ_FY;"*Start Date*";"*End Date*"; ; ; ; ; ; "Broker Recommendation (TEXT)")**
ce_aa1	Positive change in average analyst recommendation	Issuers which have a positive change in the (average) recommendation expression (buy, hold, sell etc.) in the given time window (f.ex. from hold to buy or from outperform to buy, etc.)
ce_aa2	Negative change in average analyst recommendation	Issuers which have a negative change in the (average) recommendation expression (buy, hold, sell etc.) in the given time window (f.ex. from hold to sell or from outperform to hold, etc.)

Appendix Table D: Abnormal Returns as calculated from the Market Model, using MSCI Europe Index Returns

Panel A: Private Placement Bonds (PPB), no restrictions

Window	(-10...50)	(-10...0)	(-10...1)	(-10...2)	(-10...8)	(-10...10)	(-10...15)	(-10...30)
CAAR	-0.0563	-0.0107	-0.0142	-0.0132	-0.0161	-0.0202	-0.0331	-0.054
t-Test time-series	-3.5902	-1.6089	-2.0358	-1.8182	-1.836	-2.1936	-3.2329	-4.1966
Prob.	0.0003	0.1076	0.0418	0.069	0.0664	0.0283	0.0012	0
t-Test cross-sectional	-3.8272	-1.7618	-2.2362	-2.1171	-2.202	-2.666	-3.7551	-4.3705
Prob.	0.0001	0.0781	0.0253	0.0342	0.0277	0.0077	0.0002	0
Patell Z	-3.3524	-1.6108	-2.0141	-1.6881	-1.8731	-2.1055	-3.1068	-4.1389
Prob.	0.0008	0.1072	0.044	0.0914	0.0611	0.0352	0.0019	0
Boehmer et al. (1991)	-3.3592	-1.5719	-1.9955	-1.7249	-2.0606	-2.3752	-3.5417	-4.1755
Kolary & Pynnonen (2011)	-3.1694	-1.4831	-1.8828	-1.6275	-1.9442	-2.241	-3.3416	-3.9396
Prob.	0.0015	0.138	0.0597	0.1036	0.0519	0.025	0.0008	0.0001
Corrado Rank	-2.16	-0.7206	-1.1843	-0.857	-1.0662	-1.5366	-2.3307	-2.6617
Prob.	0.0308	0.4711	0.2363	0.3915	0.2863	0.1244	0.0198	0.0078
Sign Test	-3.3752	-1.0745	-2.6673	-2.1364	-2.1364	-3.0213	-3.5522	-4.6141
Prob.	0.0007	0.2826	0.0076	0.0327	0.0327	0.0025	0.0004	0

Panel B: Public Placement Bonds (PPB), no restrictions

Window	(-10...50)	(-10...0)	(-10...1)	(-10...2)	(-10...8)	(-10...10)	(-10...15)	(-10...30)
CAAR	0.0239	0.0041	0.0021	0.0015	-0.005	-0.0048	-0.0045	-0.0021
t-Test time-series	1.6485	0.6655	0.3246	0.2191	-0.6109	-0.5618	-0.4764	-0.1758
Prob.	0.0993	0.5057	0.7455	0.8266	0.5413	0.5743	0.6338	0.8605
t-Test cross-sectional	1.3541	0.5387	0.2791	0.1991	-0.5762	-0.5611	-0.4453	-0.1965
Prob.	0.1757	0.5901	0.7802	0.8422	0.5645	0.5747	0.6561	0.8442
Patell Z	-0.3396	-0.7867	-1.0432	-1.1729	-1.6317	-1.7226	-1.6612	-1.5355
Prob.	0.7342	0.4314	0.2969	0.2408	0.1027	0.085	0.0967	0.1247
Boehmer et al. (1991)	-0.3124	-0.7874	-1.065	-1.1782	-1.6244	-1.7516	-1.6491	-1.519
Kolary & Pynnonen (2011)	-0.3082	-0.7769	-1.0508	-1.1624	-1.6026	-1.7281	-1.6271	-1.4986
Prob.	0.7547	0.431	0.2869	0.2387	0.1043	0.0799	0.0991	0.1288
Corrado Rank	-0.2362	-0.4223	-0.6115	-0.6601	-0.9098	-1.061	-1.0496	-1.1265
Prob.	0.8132	0.6728	0.5409	0.5092	0.3629	0.2887	0.2939	0.26
Sign Test	-1.0594	-1.0594	-2.1021	-1.8042	-0.7616	-1.5063	-0.7616	-0.4637
Prob.	0.2894	0.2894	0.0355	0.0712	0.4463	0.132	0.4463	0.6429

Appendix Table E: Abnormal Returns as calculated from the Market Model, using MSCI Europe Index Returns

Window	(-10...50)	(-10...0)	(-10...1)	(-10...2)	(-10...8)	(-10...10)	(-10...15)	(-10...30)
Panel A: Private Placement Bonds (PPB), high covenant intensity								
CAAR	-0.0492	-0.0063	-0.0089	-0.0114	-0.0158	-0.0214	-0.0335	-0.0503
t-Test time-series	-2.5131	-0.7527	-1.0289	-1.2569	-1.4428	-1.8649	-2.624	-3.1334
Prob.	0.012	0.4517	0.3035	0.2088	0.1491	0.0622	0.0087	0.0017
t-Test cross-sectional	-2.9153	-0.9045	-1.2503	-1.5836	-1.7782	-2.2488	-3.2364	-3.5103
Prob.	0.0036	0.3657	0.2112	0.1133	0.0754	0.0245	0.0012	0.0004
Patell Z	-2.0894	-0.9844	-1.2617	-1.4706	-1.5441	-1.811	-2.4826	-2.8601
Prob.	0.0367	0.3249	0.2071	0.1414	0.1226	0.0701	0.013	0.0042
Boehmer et al. (1991)	-2.3933	-1.0255	-1.3774	-1.6495	-1.7448	-2.0833	-3.0688	-3.234
Kolary & Pynnonen (2011)	-2.3173	-0.9929	-1.3336	-1.5971	-1.6894	-2.0171	-2.9713	-3.1312
Prob.	0.0167	0.3051	0.1684	0.099	0.081	0.0372	0.0021	0.0012
Corrado Rank	-1.7459	-0.5088	-0.813	-1.0246	-1.0636	-1.5633	-2.2362	-2.4184
Prob.	0.0808	0.6109	0.4162	0.3056	0.2875	0.118	0.0253	0.0156
Sign Test	-2.0896	0.0941	-1.6529	-1.8712	-1.4345	-2.5263	-3.3998	-3.6182
Prob.	0.0367	0.925	0.0984	0.0613	0.1514	0.0115	0.0007	0.0003
Panel B: Public Placement Bonds (PPB), high covenant intensity								
CAAR	0.0112	0.0008	0.0007	0.0001	-0.0116	-0.0109	-0.0101	-0.0148
t-Test time-series	0.5388	0.0917	0.0762	0.01	-0.9979	-0.8973	-0.7425	-0.8712
Prob.	0.59	0.9269	0.9392	0.992	0.3183	0.3696	0.4578	0.3837
t-Test cross-sectional	0.533	0.1051	0.0942	0.0201	-1.0259	-1.0055	-0.7229	-1.0713
Prob.	0.594	0.9163	0.925	0.984	0.3049	0.3147	0.4697	0.284
Patell Z	-0.2726	-0.6515	-0.6037	-0.5883	-1.0483	-1.0693	-0.9054	-1.4417
Prob.	0.7851	0.5147	0.546	0.5563	0.2945	0.2849	0.3653	0.1494
Boehmer et al. (1991)	-0.263	-0.633	-0.5915	-0.6012	-1.0183	-1.084	-0.8827	-1.4789
Kolary & Pynnonen (2011)	-0.2612	-0.6287	-0.5874	-0.5971	-1.0113	-1.0766	-0.8767	-1.4688
Prob.	0.7926	0.5267	0.5542	0.5477	0.3086	0.2784	0.3774	0.1392
Corrado Rank	0.2152	-0.1382	-0.0079	-0.1069	-0.2945	-0.5183	-0.2928	-0.9011
Prob.	0.8296	0.89	0.9937	0.9149	0.7684	0.6042	0.7697	0.3675
Sign Test	-0.4707	-0.8843	-1.2978	-0.6775	-1.091	-0.6775	-0.2639	-0.8843
Prob.	0.6379	0.3766	0.1943	0.4981	0.2753	0.4981	0.7919	0.3766

Appendix Table F: Abnormal Returns as calculated from the Market Model, using MSCI Europe Index Returns

Window	(-10...50)	(-10...0)	(-10...1)	(-10...2)	(-10...8)	(-10...10)	(-10...15)	(-10...30)
Panel A: Private Placement Bonds (PPB), with limit of indebtedness covenants								
CAAR	-0.0572	-0.0036	-0.008	-0.0115	-0.0221	-0.0315	-0.0472	-0.0607
t-Test time-series	-2.0584	-0.3059	-0.6473	-0.8995	-1.426	-1.9308	-2.5993	-2.6624
Prob.	0.0396	0.7597	0.5175	0.3684	0.1539	0.0535	0.0093	0.0078
t-Test cross-sectional	-2.5376	-0.3868	-0.8095	-1.1902	-1.853	-2.5189	-3.4115	-3.1175
Prob.	0.0112	0.6989	0.4183	0.234	0.0639	0.0118	0.0006	0.0018
Patell Z	-1.6274	-0.4292	-0.7249	-1.0123	-1.428	-1.8493	-2.3909	-2.2631
Prob.	0.1037	0.6677	0.4685	0.3114	0.1533	0.0644	0.0168	0.0236
Boehmer et al. (1991)	-1.994	-0.4525	-0.7895	-1.1656	-1.6492	-2.1967	-3.0684	-2.7043
Kolary & Pynnonen (2011)	-1.8042	-0.4094	-0.7144	-1.0547	-1.4923	-1.9876	-2.7764	-2.4469
Prob.	0.0462	0.6509	0.4298	0.2438	0.0991	0.028	0.0022	0.0068
Corrado Rank	-1.4715	0.0958	-0.2218	-0.4564	-0.8369	-1.5653	-2.2348	-2.0746
Prob.	0.1412	0.9237	0.8244	0.6481	0.4027	0.1175	0.0254	0.038
Sign Test	-2.1397	0.311	-1.0505	-1.5951	-0.7782	-2.1397	-3.2289	-2.6843
Prob.	0.0324	0.7558	0.2935	0.1107	0.4365	0.0324	0.0012	0.0073
Panel B: Public Placement Bonds (PPB), high covenant intensity								
CAAR	0.0847	0.0189	0.0206	0.016	-0.0113	-0.0066	-0.0045	-0.0038
t-Test time-series	1.6119	0.8488	0.8837	0.6582	-0.3861	-0.2137	-0.1297	-0.0876
Prob.	0.107	0.396	0.3768	0.5104	0.6994	0.8308	0.8968	0.9302
t-Test cross-sectional	1.631	1.2796	1.4144	0.9866	-0.4278	-0.2495	-0.1057	-0.0749
Prob.	0.1029	0.2007	0.1572	0.3238	0.6688	0.803	0.9158	0.9403
Patell Z	2.0265	0.8848	0.9393	0.8397	0.2599	0.3897	0.8024	0.2042
Prob.	0.0427	0.3763	0.3476	0.4011	0.7949	0.6967	0.4223	0.8382
Boehmer et al. (1991)	1.8759	1.0454	1.0729	0.936	0.2812	0.4141	0.6836	0.1987
Kolary & Pynnonen (2011)	1.6829	0.9378	0.9625	0.8397	0.2523	0.3715	0.6132	0.1783
Prob.	0.0607	0.2958	0.2833	0.3493	0.7786	0.6788	0.4942	0.8425
Corrado Rank	1.0778	0.7504	0.8093	0.6528	0.0374	0.1796	0.5183	0.2513
Prob.	0.2811	0.453	0.4183	0.5139	0.9702	0.8575	0.6042	0.8016
Sign Test	0.8438	0.471	0.0983	0.8438	-0.2745	0.471	0.8438	-0.2745
Prob.	0.3988	0.6376	0.9217	0.3988	0.7837	0.6376	0.3988	0.7837

CHAPTER III

Private Debt Fund Performance: Returns, Persistence and Alphas

Pascal Böni[90]

Abstract

This paper investigates the returns, their persistence across subsequent funds of a partnership and the alpha of private debt funds. It is based on a worldwide sample of 347 funds with vintage years 1986-2016, timed cash flow data and uses the Kaplan and Schoar (2005) public market equivalent. Over the lifetime of a private debt fund, the net of fee market outperformance amounts to 17%, on average. Annualizing this outperformance yields an average alpha (α) of 1.6%. The dispersion between top- and bottom-quartile private debt fund performance is large and goes from a market outperformance (annualized α) of +44% (+6%) to an underperformance of -16% (-2.6%). Using a one-factor market model and relaxing the Kaplan and Schoar (2005) assumption of a unit beta, I find betas reliably lower than one, indicating diversification benefits. Also and importantly, the annualized α's are considerably higher than those estimated from the Kaplan and Schoar (2005) public market equivalent and increase to 9 – 10%, significant at the 1% level. Both, quartile transition probabilities and OLS regressions of current on prior performance, indicate economically important and statistically significant persistence in returns across subsequent funds of a partnership. This persistence is driven by direct lending, special situations, distressed debt and venture debt funds. However, controlling for additional factors, I find that performance is significantly affected by credit market conditions, i.e. credit standards and funding liquidity: The public market equivalent declines by approximately -9.1% when funds are launched in times of overly loose credit standards. Likewise, it declines by -6.5% for funds launched in times of bad funding liquidity.

1 Introduction

Private capital markets have grown tremendously over the last decade. Increasingly, companies are seeking flexible terms of private funding rather than capital from public capital

[90] TIAS School for Business and Society and Tilburg School of Economics and Management, Tilburg University, the Netherlands, Remaco Group, Basel / Zürich, Switzerland

markets. This manifests itself in the number of firms traded on public exchanges and the number of Initial Public Offerings (IPOs), which are consistently going down (Gao et al., 2013; Srivastava, 2014). The evolution of new and growing alternative asset classes have caught the attention of academic researchers. For example, a large body of research analyzes private equity (PE) fund performance and its persistence (see Kaplan & Sensoy, 2015, or Korteweg, 2018, for two comprehensive reviews). On the contrary, research related to private debt (PD) is very sparse.[91]

The PD asset class gains increased attention from the media[92] and is attracting attention from consultants and institutional investors for its inclusion in portfolios. According to the Preqin (2019) report, of all investor categories listed, all are currently below their median target allocation.[93] From 2008 through 2017, PD funds have grown faster than real estate or private equity funds (see Figure 1). This growth is expected to continue and double the PD volume from USD 0.7 trillion in 2017 to more than USD 1.4 trillion in total assets by 2023 (Preqin, 2018). While the total assets of real estate funds surpassed the USD 500 billion threshold in 2011, PD has exceeded this mark in 2015 and is today comparable in total assets under management to real estate.[94] Despite the continued growth of PD assets under management of the last years (see Figure 2), to the best of my knowledge PD fund performance and its persistence have not been subject to academic analysis yet and we are still missing a comprehensive account.

Assessing PD fund performance and its persistence is a first-order concern. As with PE funds, PD investors often base their investment decisions on past performance and the belief that performance persists across funds of the same asset manager, that is, the general partner (GP) of

[91] A noteworthy exception are (Cumming et al., 2019), who analyze primary and secondary debt issuances of firms in the Asia-Pacific markets.

[92] See Financial Times, February 4, 2019, «Non-bank lenders thrive in the shadows. Explosive growth of US private debt market brings parallels to wild west.»

[93] The reported median current allocation (target allocation) amounts to 2% (3%) for asset managers, 2.5% (5%) for endowment plans, 5% (6.5%) for family offices, 1.9% (5%) for foundations, 1% (3%) for insurance companies, 1.7% (5%) for private sector pensions funds, 2% (5%) for public pension funds, 1% (5%) for superannuation schemes and 5% (8.3%) for wealth managers.

[94] According to Preqin (2018), total assets under management 2017 by asset class for private equity, private debt and real estate, to mention the most important, are USD 3.1tn, 0.7tn and 0.8tn.

a PD fund. No academic study has yet provided rigorous analysis of the public market equivalent (PME) of PD funds. Also, it is unclear whether performance persists across GPs for this asset class. Albeit widely practiced, using past performance as a naïve estimate for future performance may therefore lead to erroneous PD fund selection per se. This study aims to provide an in-depth PD fund performance and persistence analysis. In addition, it provides an analysis which factors, other than persistence, affect fund performance. This is important given the strong growth of this asset class and the closed end nature of PD funds, the latter leading to long-term capital commitments of generally ten plus years from investors.

This paper analyses 347 PD funds from vintage years 1986 through 2016. It is based on a sample of 117 mezzanine, 54 direct lending, 32 special situations, 127 distressed debt and 17 venture debt funds.[95] The average fund size is 1,342 million US dollars (in 2018 dollars) and the main geographic investment focus is the United States (84%), followed by Europe (13%) and Asia (3%). Fund data is provided by Preqin, a commercial data provider and data source that is increasingly used for the purpose of academic research.

As in PE studies, the analysis of the data is inherently complicated by the fact that returns can not be observed on a regular basis. Also, cash flows are highly skewed. Additionally, analysing cash flow data involves taking a stand on the fair market value of unrealized assets of a PD fund as long as one does not limit the analysis to fully liquidated funds. The latter is the case in this study. For the purpose of calculating fund performance, self-reported and unrealized net asset values (NAVs) are treated in two ways. First, they are treated as market values as in Kaplan and Schoar (2005) or Harris et al. (2014a), that is, as liquidating distribution to investors. Second, to address the academic debate around the various practices related to NAV valuations (see, for example, Phalippou and Gottschalg , 2009; Stucke, 2011; Driessen et al.; 2012, Jenkinson et al. 2013; Brown et al., 2017; Barber & Yasuda, 2017), unrealized NAVs are adjusted to reflect a potential upward bias in fair market values. Motivated by prior research, unrealized NAVs of PD

[95] These are investment strategies described in more detail in the Appendix to this paper.

funds that are not fully liquidated are written down by 5%, and those of PD funds beyond their typical liquidation age by 30%. On the one side, these write-downs should reflect potential biases arising from potential NAV manipulation by GPs in times of fund raising, which Barber and Yasuda (2017) find to amount to approximately 5% in the PE fund industry. On the other side, the 30% write-down of unrealized NAVs is motivated by the findings of Driessen et al. (2012), who estimate that NAVs of PE funds beyond their typical liquidation age are substantially overvalued.

To assess how PD funds perform and whether they out- or underperform the markets, I provide a number of performance calculations using absolute and relative performance metrics.

Performance. As investors still focus more on absolute performance as opposed to risk-adjusted returns (Gompers et al., 2016) and to accommodate typical fund investors' habit of analysing performance, the internal rate of return (IRR) and the total value to paid in capital (TVPI) are calculated for each PD fund. On average, PD funds provide an IRR of 10.6% and a TVPI ratio of 1.4. Distressed debt funds with an IRR of 12% provide higher performance than special situations / mezzanine / direct lending / distressed debt and venture debt funds with an IRR of 11%/ 9% / 10% / 11% and 8% respectively. While the best funds provide an IRR (TVPI) of 23% (1.8X), the worst distribute as much money to investors as they previously collected from them. Their IRR (TVPI) amounts to 0% (1.0X). This dispersion appears to be independent of fund type as mean (median) performance metrics are relatively close to each other.

Whilst useful, absolute performance measures suffer from a number of drawbacks and do not adjust for risk. More recent literature gravitates towards stochastic discount factor (SDF) approaches and relative or market-adjusted performance.[96] In this vein, this study follows two methodological approaches in measuring risk-adjusted performance. First, it follows Kaplan and Schoar (2005) in calculating the public market equivalent (PME), based on timed fund cash flows and using two alternative benchmark indices. Second, a generalized method of moments

[96] See Kaplan and Sensoy (2015) or Korteweg (2018) for two surveys on the literature on PE performance, for example, that note this methodological shift towards the use of a SDF and market adjusted performance.

procedure (GMM) is deployed to estimate the abnormal return (alpha, α) and beta (β) of PD funds as in Driessen et al. (2012).

Turning to relative performance as measured by PME, PD funds show an average market outperformance of 12% over the lifetime of a PD fund[97] and an annualized alpha of 2% when compared to the Bloomberg Barclays US Corporate Bond Total Return Index (PMEIG), which provides a benchmark for investment grade bonds. Benchmarked to the Bloomberg Barclays US Corporate High Yield Index ("PMEHY"), the cross-sectional lifetime outperformance (PME) drops to 7% or an annualized excess return of 1% respectively. The large dispersion between top- and bottom quartile funds shown earlier is confirmed: For top-quartile funds, the average lifetime outperformance / annualized alpha as measured by the PMEIG (PMEHY) amounts to 44% (37%) / 6.0% (4.9%). Bottom-quartile funds provide an underperformance / annualized alpha of -16% (-20%) / -2.6% (-3.2%). Sorted by vintage years, the average PME as compared to the investment grade benchmark is 17%. This translates into an annualized alpha of 1.6%. Benchmarked to the high yield benchmark, investors profit from a market outperformance (annualized alpha return) of 12% (0.9%), on average.

The estimation of cross-sectional abnormal returns (α) and systematic risk (β) as in Driessen et al. (2012) is used to relax the assumption of a beta equal to one as in Kaplan and Schoar (2005). It appears that betas of PD funds are lower and reliably different from one in the cross-section. This indicates diversification benefits from PD funds. Also, it appears that the annualized alphas as estimated with the Kaplan and Schoar (2005) PME may be downward biased. Finding high alphas and using a capital asset pricing model (CAPM) logic, PD funds therefore provide value to investors in that they have returns well in excess of their cost of capital.

Persistence. Given the relatively attractive top-quartile performance of PD funds, it would be interesting to know whether past performance is indicative of future PD fund performance. The persistence of PD fund performance is therefore evaluated in a next step. Persistence of returns

[97] For brevity, the total market outperformance over the lifetime of a PD fund shall also be called "lifetime outperformance" or "market outperformance".

across successive funds of the same GP is calculated using a regression framework and the calculation of transition probabilities based on performance quartiles, methodologically as in Kaplan and Schoar (2005) or more recently in Harris et al. (2014b). Focusing on PME, which is (Lerner et al., 2018, p. 17) “the standard performance measure used in the academic literature”, I find significant persistence. In the cross-section, a 10% increase in lagged performance increases current performance by an approximate 2%, the coefficient being highly significant. Moreover, persistence appears to be driven by positive lagged performance, not negative lagged performance, and by the post-2007 period.

Calculating transition probabilities, GPs with a previous fund in the top-quartile are expected to remain in this quartile with their next fund with a probability of 50% and for the post-2007 sub-period. For the pre-2007 period, this probability is lower and amounts to 30%. Interacting fund type with previous fund performance and repeating the fund persistence regressions, previous fund performance appears to be a significant predictor of current fund performance for direct lending, special situations and distressed debt funds, the coefficients on the lagged performance being significant at the 1%, 5% and 5% level respectively. For these fund types, it appears to be a good strategy to invest in PD funds managed by GPs that have previously managed top-quartile funds. Relative to a randomized strategy and calculated from quartile transition probabilities, the average increase in market outperformance as measured by PME to be achieved from such prediction would have been 8% for the overall sample period and 13% for the post-2007 sub-period.

Factors affecting performance and persistence. Although not the main focus of this study, I also control if and how several fund specific factors (such as fund type, industry focus, geographical focus or size) and credit market conditions (such as funding liquidity, credit standards, the aggregate amount of capital flowing into the PD industry and recessionary market periods) affect fund performance. Methodologically, I follow Kaplan and Strömberg (2009) who show that factors such as capital inflows in the early life of a fund can explain realized returns during the subsequent ten- to twelve-year period. Univariate and multiple OLS regressions of fund performance as measured by PME on a set of factors measured for the vintage year (t) and the subsequent year (t+1) are used. The results suggest that credit market conditions observed for t and t+1 significantly impact a fund's performance but also persistence.

First, I test how loose (tight) credit standards affect performance. The data are from the US Federal Reserve quarterly survey and indicate the net percentage change of reported senior loan officers' standards (SLOS), i.e. tightening or loosening credit standards for loans. This variable (see Axelson et al., 2013) is a proxy for nonprice aspects of credit market conditions, such as debt covenants and quantity constraints. I find that PD funds launched in years allowing for very loose credit standards (at the 10th percentile of SLOS) perform worse by approximately 9.1%. A potential explanation for the observed relationship is that PD funds that invest in times of loose credit standards may find it difficult to renegotiate their initial lending contracts in the later stage. Lower covenant protection and fewer quantity constraints might affect PD fund performance negatively.

Second, I control for the market's funding liquidity as measured by the TED spread, which is the difference between the interest rates on 3 months US government debt and interbank loans. TED spread appears to be an incrementally strong predictor of future PD fund performance. If investors requiring higher or lower rates in compensation for higher or lower systemic liquidity in years t and t+1, TED spread should be positively related to performance. However, I find that an increase in TED spread (worsening of funding liquidity) is negatively related to PD fund performance: a 10% worsening of funding liquidity reduces performance by 1.3%. Funds launched in market states of bad funding liquidity show a PME that is reduces by approximately 6.5%. A potential explanation for this negative sign is that funds may find it difficult to refinance their portfolio in times of low funding liquidity and be confronted with higher borrowing costs, translating into lower returns.

Other credit market conditions such as global risk (credit spread) or the aggregate amount of capital flowing into the PD industry are controlled for. They appear to leave PD fund performance unaffected. These findings are robust to a set of additional tests explained in the robustness section.

Given the used methodology as in Kaplan and Strömberg (2009), I only measure credit market conditions of periods t and t+1, i.e. for the vintage year and the following year. Any one proxy for expected PD fund performance is therefore noisy. Although the presented results are strong, it must be cautioned against overinterpreting them. Nevertheless, the presented findings related to credit market conditions are suggested to be illustrative of broader patterns and the data suggests that the main factors affecting PD fund performance beyond persistence are credit standards and funding liquidity.

This study contributes to the sparse literature on PD funds in that it provides information on the market outperformance of PD funds using the Kaplan and Schoar (2005) PME. It advances our understanding of the risk and return of the fast growing PD asset class in that it calculates annualized alphas (α), both by deriving them from cumulative alphas calculated from the PMEs and by application of the Driessen et al. (2012) method to estimate risk and return of nontraded assets. Moreover, it analyses performance across funds managed by the same GP. Using the PMEs of PD funds quantified in the first part of this study, it answers the question whether past market outperformance can be used as a naïve estimate of future PD fund performance. Furthtermore, it provides information how credit market conditions affect the outcome of such estimations. Finally, it shows that PD fund performance persistence is not declining with increasing competition, as was the case with PE funds.

The rest of the paper is organized as follows. I start the paper by describing how the private debt industry works (Section 2), followed by the review of related literature in Section 3. In section 4, I discuss the data used and provide an outlook of the methodologies used. In Section 5, descriptive statistics and PD fund performance is presented. Section 6 explores persistence, followed by section 7, in which several factors affecting PD fund performance are assessed. A set of robustness tests are provided in Section 8. Section 9 concludes this paper.

2 Private Debt Funds, Firms, Investors and Fees

PD funds are organized much like PE funds.[98] PD funds are financial intermediaries that pool investors' capital and make investments in portfolio companies that are typically private companies. These investments include a variety of debt-like instruments. Funds are organized as limited partnerships (LPs), managed by an asset manager (the general partner, GP) and have a contracted life in many cases around ten years, which is often extended upon mutual agreement between LPs and GP for an additional time period. The year the fund makes its first capital calls is referred to as vintage year, followed by an investment period in the first years of a PD fund's life. Subsequent years are then devoted to manage redemptions and exit debt investments. The fund returns originate in cash coupons (mostly fixed rate and paid regularly), payments in kind (typically accrued interest paid at the end of a financing agreement), upfront fees collected at the origination of a financing contract, and penalty fees, which are usually asked from a borrower if a financing agreement is repaid prior to maturity. While many PD funds follow a buy-and-hold strategy, some also buy and sell debt in secondary markets. This may additionally impact the returns of PD funds. While investors in PD funds can not redeem their investment prior to the contracted lifetime of the fund, redemptions of debt contracts and interest payments at the portfolio level are typically distributed directly to LPs, that is, they do receive cash distributions over the lifetime of a fund.

GPs receive fee payments from their LPs, deducted directly from the fund assets and influencing cash flows and hence performance. Although I use net-of-fee cash flows in this study to calculate performance, it is interesting to shed light on the general fee structure of PD funds. Typically, PD fund fee payments consist of a fixed management fee, which is not based on the performance of the fund, and an additional performance based variable fee. According to Preqin Pro (2019), the average (median) fixed management fee of closed end PD funds (n=588) amounts to 1.7% (1.8%). The average (median) performance fee (n=542) amounts to 19.2% (20%) and is

[98] See Kaplan and Strömberg (2009) for a review of how PE firms and funds function or Zimmerman (2015), figure 1, for a graphical illustration of the PE capital investment cycle.

typically charged to the return in excess of a preferred return to LPs. This preferred return is preset in the prospectus at the inception of a PD fund. Of the reporting funds (n=420) the average (median) preferred return is 7.6% (8%). Management and performance fees as well as the preset return are comparable to those extensively studied in private equity, for example by Gompers & Lerner (1999), Metrick and Yasuda (2010), Robinson and Sensoy (2013) or Robinson and Sensoy (2016). In these PE studies, a clustering of average management fees of around 2%, average performance fees of approximately 20% and average hurdle levels of 8% are observed.[99]

It appears surprising that PD GPs generate a compensation comparable to that of PE GPs. One could expect that investing in debt is different from and less intensive than investing in equity. However, as is illustrated in Deloitte (2019), more than two thirds of all direct lending transactions in Europe are mergers and acquisitions related and do involve a private equity sponsored transaction. On a global basis including all geographies, approximately 73% of all PD fund transactions are sponsored transactions. A large fraction is driven by buyout financing (46%), growth financing (22%) and public to private transactions (3.3%). Only about 13.4% of all PD transactions are based on recapitalization needs of corporates. Also, only about 20.4% of all PD transactions involve senior debt, leaving almost 80% to subordinated and mezzanine debt and other special transaction types.[100] Thus, the majority of PD transactions are complex and different from bank lending and involve corporates making transformational acquisitions, seeking growth capital, aiming to consolidate their shareholder base or raising junior debt / debt subordinated to bank debt. Investments are habitually done in sub-investment grade firms and involve SME transactions. The value creation process of PD funds is very much comparable to that described

[99] Various other fee components exist in PE but also in PD. For example, fees depend on the carry basis, which describes the standard by which profits are measured and the carry timing, which refers to the set of rules that govern the timing of carried interest distributions. Also, many PD funds request portfolio companies to pay drawdown fees, monitoring fees and transaction fees (see, for example, Phalippou et al., 2018), which are sometimes distributed to the PD fund and sometimes to the GPs, thereby affecting fund performance and potential agency conflicts between GPs and LPs. However, this paragraph provides an introduction to the economics of PD funds only and a more detailed description of fee components and structures lies beyond the focus of this study.

[100] see Preqin Pro, August 12, 2019. Deal level data are from approximately 15,000 transactions.

in Gompers et al. (2016) and for PE funds. It involves financial engineering activities (valuation, capital structure advisory and incentive management at the portfolio company level), governance engineering (board composition, monitoring, hiring and firing of top management) and operational engineering and value creation.

Also, the PD asset class stands up to a comparison with the PE asset class in terms of size and investor sophistication. In recent years, PD funds have raised large amounts of investor capital. Albeit somewhat smaller than PE funds, according to Preqin Pro (2019), the 30 largest PD fund managers raised a very large average of USD 13.9 billion per fund and a total amount of USD 416 billions in the last ten years (see Appendix Table 1, Panel A).[101] The three largest of them exceed the amount of USD 30 billions (Oaktree Capital Management, Goldman Sachs and GSO Capital Partners) whilst the three smallest (EQT, Kayne Anderson Capital Advisors and Strategic Value Partners) each raised capital in excess of USD 5 billion. As of January 2019, the 30 largest funds together have approximately USD 144 billion ready to invest but not yet allocated, thus, the PD fund market is currently looking for attractive debt investments and highly competitive. As is shown in Panels B through E of Appendix Table 1, the largest PD fund managers are domiciled in the US (Panel B), followed by those in Europe (Panel C). Asian (Panel D) and rest of the world fund managers (Panel E) are much smaller in size and estimated dry powder. Appendix Table 2, Panels A through E, shows the largest PD funds according to their geographical focus. They are primarily focused on North-America and Europe (Panels A through C) and to a lesser extent on Asia and the rest of the world (Panels D and E). As is shown in Appendix Table 3, investors are typically fund of funds, public and private pension funds, banks, insurance companies and sovereign wealth funds. The largest investors are domiciled in Switzerland, followed by the US and Canada and to a lesser extent in other regions (see Panels A through D). Interestingly, the largest endowment plan investors in PD funds (Panel E) are public institutions (Church Commissioners for England, Texas Treasury Safekeeping Trust Company) or University endowment funds (University of Chicago

[101] Compared to private equity (PE) funds and according to Preqin Pro (2019), this compares to approximately USD 1.4 trillion in total and USD 46 billions on average in fund raising over the last ten years and for the 30 largest PE fund managers.

Endowment, Northwestern University Endowment and Oxford University Endowment). These institutions appear to invest larger amounts into PD funds as US family offices (Panel F) and amounts comparable to insurance companies (Panel G). Within the pension and sovereign wealth funds, US public pension funds (Panel I) appear to dominate the investor landscape, followed by large UK private pension funds (Panel H) and sovereign wealth funds across the world (Panel J).

Overall, it appears that the structure, fee level, value creation process as well as the size and investor sophistication of PD funds are very much comparable to those of PE funds.

3 Related Literature

Fund performance and its persistence are a critical issue for investors in their choice of fund managers. The equity mutual fund literature has reached a consensus that performance, net of fees, is negative and just well enough to cover the costs (Eugene F. Fama & French, 2010; Wermers, 2000). Persistence in fund performance has been difficult to detect. Malkiel (1995), for example, finds that while persistence was considerable in the 1970s, there was no consistency in returns during the 1980s.[102] Similarly, performance persistence for hedge funds is little or modest (see, for example, Bares et al., 2002; Brown et al., 1999; Edwards & Cagalyan, 2001; Kat & Menexe, 2002) and on average, net alphas are zero (Fung et al., 2008).

An asset class for which both, performance persistence and positive alphas have been detected, tested and in which the persistence claim withstands academic scrutiny appears to be private equity (PE). PD funds are much like PE funds in terms of organizational structure, cash flow distribution and inherent potential agency conflicts between GPs and LPs (such as for example NAV manipulation). I therefore take advantage of the methodologies applied in the PE related studies. These are described in section 3.1. Prior literature on PD funds and additional literature

[102] See also Carhart et al. (2002), who provide a comprehensive review of this topic, basically confirming the findings of Malkiel (1995).

deemed relevant to the analysis of PD fund performance and its persistence is then summarized in section 3.2.

3.1. Prior literature on private equity (PE) funds

Early contributions to the understanding of PE performance have been provided by Kaplan and Schoar (2005) and Phalippou and Gottschalg (2009).[103] Kaplan and Schoar (2005) examine a sample of PE funds with vintage years beginning in 1980 until 1997. They focus on the public market equivalent (PME) as performance measure. It is calculated as the ratio of the sum of discounted distributions to the sum of discounted contributions. The discount rate is the total return on the relevant market benchmark. A fund with a PME greater than 1 and net of all fees outperforms the market, a fund with a PME less than 1 underperforms it. The PME thus provides a cumulative measure of performance. For example, a PME of 1.2 means that an investor earns 20% more by investing in a fund rather than the public market benchmark. Kaplan and Schoar (2005) find that overall PE returns are approximately equal to the S&P 500. Additionally, they find that large differences in the returns of individual funds ranging from a 3% cash flow IRR at the 25th percentile to one of 22% at the 75th percentile exist. In a second analysis, they show that repeating performance is not random. They use two methods to provide evidence of performance persistence. First, they employ OLS regressions of current on previous fund performance. Second, Kaplan & Schoar (2005) calculate the probability of repeating top-tercile (bottom-tercile) performance and find that it amounts to 55% (44%). Moreover, they suggest a concave relation between fund size and performance, implying that when funds become very large, performance declines. Like in this study, Kaplan & Schoar (2005) use quarterly cash flow data to calculate PME. For the purpose of calculating performance, Kaplan and Schoar (2005) treat last-observed net asset values (NAVs) of funds as a liquidating distribution to investors.

Contrasting Kaplan and Schoar (2005), Phalippou and Gottschalg (2009) claim that treating NAVs as accurate estimates of fund market value creates a performance bias and recommend

[103] For a review of additonal early studies analyzing PE performance see Kaplan and Sensoy (2015).

writing them off when calculating the performance of largely liquidated funds. In doing so, they find that average fund performance decreases. Support for the views of Pahlippou and Gottschalg (2009) is presented by Driessen et al. (2012), who estimate that self-reported NAVs for funds beyond their typical liquidation age may significantly deviate from market values. They predict that NAVs of mature and inactive funds significantly overstate fund values and are around 30%. Additionally, they propose a new method to estimate alphas and betas of nontraded assets from cash flows for PE funds. Driessen et al. (2012) use a discount rate for contributions and distributions equal to the risk-free rate plus the alpha to be estimated and the excess market return times beta to be estimated and minimize the sum of squared differences between the present value of a fund's contributions and distributions.

Stucke (2011) contrasts Phalippou and Gottschalg (2009). He re-examines the PE data and finds that self-reported NAVs in previous studies were wrong because funds ceased to update their data in the database. He collects the true cash flows and NAVs for a large portion of the previously researched funds from LPs and finds NAVs greater than those reported in the database. Not surprisingly, he finds performance which is markedly better than that calculated by Kaplan and Schoar (2005) or Phalippou and Gottschalg (2009) and concludes that the estimates of these two studies are downward biased because of missing true cash flows and self-reported NAVs.

More recently, Jenkinson et al. (2013), Brown et al. (2017) and Barber & Yasuda (2017) have found that NAVs are usually conservative. However, they appear to spike around likely fundraisings and in the fourth quarter of the year (Jenkinson et al., 2013), are more conservative for top performing funds (Brown et al., 2017) and are used by GPs to time subsequent fundraisings, after which size and frequency of NAV markdowns increase (Barber & Yasuda, 2013).

This paper is also related to Sensoy et al. (2014), Harris et al. (2014b) and Braun et al. (2017), who analyze, amongst other aspects, how the maturing of the PE industry has changed performance and persistence. Sensoy et al. (2014) show an industry-wide decline in returns and a decline in the relations between GP experience and return. They analyze performance at the GP level. Harris et al. (2014b) confirm persistence in pre-2000 funds. For post-2000 funds they find little evidence of persistence in fund returns. Braun et al. (2017), using portfolio company cash flows instead of fund level cash flows, also evidence that persistence has substantially declined as the PE sector has matured and become more competitive.

A number of additional recent studies investigate other aspects of PE performance and persistence based on the PME. Harris et al. (2014a), using stated NAVs in their analysis of Venture Economics data, confirm the lifetime outperformance of public markets by US buyout funds and find large time variation for venture funds, with outperformance in the 1990s but underperformance in the 2000s. Moreover, they show that fund performance is significantly negatively related to capital commitments: an increase from the bottom quartile of years to the top quartile of years of capital influx declines IRRs by more than 5% per year. Kaplan and Strömberg (2009) provide another study that observes a strong negative relation between fundraising and PE fund performance. Phalippou (2014), shows the sensitivity of fund performance to the choice of the benchmark. Using a micro-cap mutual fund as a benchmark, he finds that the average and median PME fall to 1.04 and 0.99 respectively, suggesting that the average buyout fund return is similar to that of similar sized listed equity. In this vein, L'Her (2016) study PE buyout fund performance. Using a bottom-up approach, they identify the systematic risks of underlying companies in buyout funds to inform an appropriate risk-adjusted benchmark. After making several risk adjustments, they find no significant outperformance of buyout fund investments versus the PME. Harris et al. (2018) identify outperformance at the fund of fund level. Further, Robinson and Sensoy (2016) investigate cash flow liquidity and find substantial comovement with public markets: contributions from and distributions to limited partners of PE funds both have a procyclical systematic component. Also, they find that funds raised in hot markets underperform those raised in bad times, the explanation rooted in a liquidity premium for calling capital in bad times. Ang et al. (2018) decompose PE returns into a component due to publicly traded factors and a time-varying PE premium and find that time series variation in PE returns is highly cyclical and differs across subclasses of PE.

3.2 Prior literature on private debt (PD) funds

Somewhat surprisingly, other than with PE funds, PD fund performance has not been researched a lot. Carey (1998) investigated a portfolio of private loans and found that it has lower default and higher recovery rates than a portfolio of public bonds with equivalent risk. His study is based on the data of 13 major life insurance companies in the US, sampling loans from 1986 to 1992. The study of Carey (1998) does not cover a time period in which the PD fund industry evolved. Observed PD fund activity starts in 1986 and years with more than 5 PD funds raised per vintage year are only observed approximately 10 years later, that is from 1996 onwards. Cumming and Fleming (2013) and Cumming et al. (2019) are two studies related to PD loans provided by two institutional investors and specialist credit investment funds. Cumming and Fleming (2013) document the performance of 311 loans used by private firms across 25 countries over 2001-2010. According to them, performance depends on the portfolio size per manager, highlighting the role of time allocation for due diligence and monitoring. Additionally, performance according to them is related to borrower (firm-specific) risk. By contrast, they find that market conditions such as TED spreads and country level legal factors such as creditor rights are insignificantly or weakly related to the returns to private debt. Cumming et al. (2019) study more than 400 loans acquired through new issuances or secondary market transactions. They analyse data at the transaction level in 13 Asia-Pacific markets between 2001 and 2015 and find that trading private debt delivers higher returns than buying and holding a primary issuance. Additionally, they create an index and find that private debt investments deliver excess returns to public markets over time, these excess returns being affected by volatility, funding liquidity, and the global financial crisis (GFC).

Carey (1998), Cumming and Fleming (2013) and Cumming et al. (2019) study debt performance at the loan level. However, the PD industry has seen an immense growth in PD funds, creating the necessity to analyse performance at the fund level. To the best my knowledge, only one study has researched the performance of PD funds. Munday et al. (2018) use the Burgiss database and analyse 476 private credit funds together with a subset of 155 direct lending funds.

They find positive IRRs for the top three quartiles across all investment strategies and relatively low beta and positive alpha using leveraged loan or high yield indices, indicating diversification benefits. The study of Munday et al. (2018) does, however, not investigate a fund's persistence in performance, nor does it control for factors affecting performance or persistence.

3.3 Additional literature

It appears that another strand of literature is relevant to the analysis of PD fund performance. Credit market conditions, such as the aggregate amount of capital flowing into the PD fund industry, bank loan supply, loan conditions or credit standards, affect firms' ability to access external finance. In this study, I cover a period before and after the global financial crisis (GFC), thus providing information about different states of bank loan expansion and contraction and credit market conditions. For example, Leary (2009) provides evidence that following an expansion (contraction) of bank loan supply, the bank loan ratio of small and bank-dependent firms significantly increases (decreases) relative to that of large, less bank-dependent firms. Lemmon and Roberts (2010) show that substitution to alternative sources of capital given contraction in the supply of credit is limited, leading to an almost one-for-one decline in net investment for below-investment-grade firms. Duchin et al. (2010) study the effect of the global financial crisis (GFC) and negative shocks to the supply of external finance on corporate investment. They find that corporate investment declines significantly following the onset of the crisis, this decline being largest for firms that operate in industries dependent on external finance. This finding is confirmed by a later study of Carvalho et al. (2016), who additionally suggest that public debt markets do not mitigate the effects of relationship bank distress during financial crises.

Is appears that important and large gaps exist in the PD fund literature First, to the best of my knowledge, no prior research has calculated PD fund performance using timed cash flow data. Analysing cash flows from and to the LP allows to calculate the public market equivalent (PME) of PD funds and net of fees. Second and obviously related to the first deficit, no prior research has yet analysed the persistence of performance across funds managed by the same GP. However, this information is needed to gauge for the accuracy of using past performance as a naïve estimate of future performance. Third, the examination of the question how credit market conditions affect PD fund performance is missing. Fourth, it is unclear whether persistence for PD funds is declining with increasing competition, as was the case with PE funds. This study aims to shed light on these research gaps and contributes to closing them.

4 Data & Methodology

This study uses an extensive worldwide PD data set including timed cash flows obtained from Preqin. It provides fund level as well as GP level information such as performance, size, type and geography, firm inception etc.

4.1 Data

Cash flow data is made available by Preqin. This cash flow data is gathered from reliable sources such as U.S. pension funds and obtained via Freedom of Information Act (FOIA) requests. Cash flow data from Preqin is increasingly used in academia and found to be reliable.[104]

As Braun et al. (2017) remark, any data source that relies on GPs to reveal their returns is subject to biases that arise from the lower probability of revealing the past performance of funds that performed poorly. Also, to the extent that data from GPs are back-filled, there are survivorship biases. Given that not much research related to PD funds is available, little is known about the extent of attrition among GPs focused on PD funds. The fact that data for this study are

[104] See, for example, Phalippou (2014), Barber & Yasuda (2017) or Ang et al. (2018). Phalippou (2014), for example, compares the Preqin cash flow dataset with the proprietary datasets of Harris et al. (2014a) and Higson and Stucke (2012) and finds that the average PME of PE funds using the different datasets is very similar. Similarly, Ang et al. (2018) calculate PMEs by vintage year and based on Preqin data and compare their results to those of Harris et al. (2014). Ang et al. (2018) report that the output statistics are extremely close. As is reported in Korteweg (2018), out of 14 scientific studies analyzing fund-level (or LP level) PE returns, 4 use the Preqin database. Given the findings of Phalippou (2014) and Ang et al. (2018) and the review in Korteweg (2018), a priori, it appears prudent to base this study on Preqin cash flow data.

gathered from reliable sources such as U.S. pension funds and obtained via Freedom of Information Act (FOIA) may invalidate some of the concerns of Braun et al. (2017) partially. Gathering the data in this way is comparable to Harris et al. (2014a), for example, who rely on Burgiss data, sourced from more than two hundred institutional investors. Such data appear unlikely to suffer from any major biases. However, survivorship biases can not be excluded. I therefore control for potential survivorship effects as attrition might affect PD fund performance. Specifically, I control for the performance effects of first generation funds and one-time funds. First generation funds are those funds for which data has entered the Preqin database for the first time, followed by successive funds managed by the same GP. One-time funds are funds that enter the sample once but for which no subsequent fund is observed. After their first listing, GPs of one-time funds disappear from the sample. Of the 347 PD funds, 75 are one-time funds with no subsequent fund and 77 are first generation funds, followed by successive funds. I will show later that first-time fund performance is significantly better than one-time fund performance and that accounting for PD fund survivorship, performance increases in the cross-section.

4.2 Sample

Special attention is given to the fact that of 921 PD funds reported in Preqin,[105] performance data (IRRs and multiples) is only available for approximately 820 funds and cash flow data solely for 396 or only 43% of all PD funds. As reported in the robustness section, I find no upward bias in the data used in this study when comparing the results to the Preqin database. This limits the concern that only performing funds make cash flow data available while the non-availability of data of some PD funds could be driven by GPs not disclosing poor past performance. I address this point later in the robustness section and show that the used fund performance information appears to be conservative.

Since this study uses cash flows to calculate relative performance (PME), funds that do not provide cash flow information are eliminated from the sample. Moreover, I eliminate 48 funds

[105] As per October 1st, 2018.

with a lifetime shorter than one year since these funds have only just started their investment activity and, therefore, are unlikely to have had sufficient time to deliver meaningful performance. The final sample consists of 347 PD funds managed by 157 GPs. The funds follow an investment strategy broken down into five distinct although not mutually exclusive fund types. These are mezzanine (117), distressed debt (127), direct lending (54), special situation (32) and venture debt (17). The sample size of this study is comparable to early research on the performance of private equity funds. Kaplan and Schoar (2005), for example, draw conclusions on the performance of buyout (VC funds) using a sample of 169 (577) funds.

The sample covers vintage years 1986 through 2016 and therefore also includes relatively young PD funds with more recent vintage years. By construction, these younger funds have high portions of unrealized remaining values (NAV) in relation to the total paid-in contribution of a LP (RVPI). Other researchers have included funds with high RVPI, for example Harris et al. (2014a).[106] This may raise concerns related to the valuation of unrealized fund assets. I deviate from Kaplan and Schoar (2005) or Braun et al. (2017),[107] who focus on largely liquidated funds. The chosen vintage year cut-off and inclusion of funds with relatively high RVPI has several advantages. First, it increases sample size. This is a necessary condition for most of the analyses presented. Using fully liquidated funds would reduce the sample size to 26 PD funds launched in vintage years 1986 through 1997. Second, given that PD funds have seen a huge increase in number and size in more recent years, including funds with higher RVPI allows to provide performance data on more recent PD funds and avoids a bias towards funds launched prior to the Global Financial Crisis (GFC), which eclipsed the fundraising of PD funds. Finally, the longer observation period allows the analysis of time variation in PD fund performance over a 30 year horizon, including the analysis of periods of recession as identified by the National Bureau of Economic Research (NBER).

[106] Harris et al. (2014a) report a median RVPI for their last four sample years of 90.3%, 89.2%, 98.1% and 93.7% (see Table II).

[107] Braun et al. (2017), for example, include funds in which at least 50% of the capital invested has been realized.

The inclusion of funds with higher unrealized values appears diligent for additional reasons. First, with the introduction of topic 820 of the Financial Accounting Standards Board (FASB) by the end of 2009, funds are required to value their assets at fair value every quarter, rather than valuing them at cost.[108] As Harris et al. (2014b, p. 5) note “This has likely had the practical effect of making estimated unrealized values closer to true market values than in the past […].” Funds with unrealised values in excess of 50% have vintage years 2011 and beyond and are therefore launched after the introduction of topic 820. Unrealized values should therefore approximate true market values. Second, there is empirical evidence that unrealized values are, on average, conservative. Jenkinson et al. (2013) and Harris et al. (2014a) deem unrealized NAVs to be conservative or close to fair market values. Robinson and Sensoy (2016), for example, calculate performance statistics using smaller and fully liquidated samples containing no self-reported NAVs and compare them to larger samples including self-reported NAVs. They conclude that their performance statistics are almost identical (p. 526): “pre-liquidation NAVs, although self-reported by GPs, are not generally biased estimates of the realized market value of the fund.” Brown et al. (2017) also find that top-performing funds under-report returns and suggest that, on average, unrealized values are conservative. They observe that NAV manipulation is primarily a problem with poor performing funds. These make up roughly 15 percent of all funds in their sample. As I will show later in the robustness section, using only largely liquidated funds does not materially affect the findings of this study.

To accommodate potential concerns related to the fair value of self-reported NAVs, however, and to gauge the potential effect from NAV manipulations, an adjustment to residual values is considered. This adjustment is based on the findings of Driessen et al. (2012), Jenkinson et al. (2013), Brown et al. (2017) and Barber and Yesuda (2017): Driessen et al. (2012) find that self-reported NAVs of non-liquidated PE funds beyond their typical liquidation age may deviate substantially from their real market values. Jenkinson et al. (2013) find that periods in which

[108] See the more recent update 2018-13 of the FASB which introduces some modifications and additions related to topic 820 and the changes in unrealized gains and losses to develop fair values.

follow-on funds are being raised are the exception to general conservatism and lead to inflated self-reported NAVs. In the same vein, Brown et al. (2017) evidence that reported unrealised values may be manipulated and boosted during times that fundraising activity is likely to occur. Barber and Yasuda (2017) evidence that NAVs of PE funds are exaggerated by up to 5% in times of fundraising. Motivated by these findings and to avoid a potential upward bias in performance measures, I calculate adjusted IRRs using the LP cash flow data provided by Preqin and correct the unrealised fair value, that is the self-reported NAV calculated by the GP. The latter is considered the firm's opinion rather than a market value. Instead of treating the self-reported NAVs as a market value and final cash flow as in, for example, Kaplan and Schoar (2005) or Harris et al. (2014a) or writing them off completely as in Phalippou and Gottschalg (2009), this study adjusts self-reported NAVs: First, I write down the unrealised NAV by 5% for all funds that are not beyond their typical liquidation age and that are not liquidated. The 5% write-off rate is taken from Barber and Yasuda (2017) and accounts for potentially exaggerated NAVs in times of fundraising. Second, motivated by the findings of Driessen et al. (2012) or Phalippou and Gottschalg (2009), self-reported NAVs of funds that are beyond their typical liquidation age, that is the median age of the cross-section, are written-off by 30%. This write-off rate is based on studies related to recovery rates for defaulting debt instruments (Chen, 2010; Van de Castle et al., 2000; Davydenko et al., 2012; Altman et al., 2005) and an estimate related to the probability of default based on the findings of Robert and Sufi (2009) as explained in more detail in **Appendix II**.

Several reasons may justify an adjustment of NAVs lower than that estimated for PE funds by Driessen et al. (2012) or recommended by Phalippou and Gottschalg (2009). First, the expected payoffs for different asset classes are increasing with seniority. Other than with PE funds, the assets of a PD fund typically rank higher than those of a PE fund and may in some cases be secured or partially secured by company assets. The market value of such debt assets, even for PD funds beyond their typical liquidation age, might therefore be higher than that of equity-like assets. Second, according to Preqin (2017), the valuation of NAVs should be carried out in accordance with IFRS, GAAP, FAS 157 and/or the relevant industry guidelines such as for example the International Private Equity and Venture Capital (IPEVC) guidelines. Also, the aforementioned FASB requirements apply to PD funds and asset valuations appear to be more objective when applied to debt instruments which will typically have a face value and which are less prone to subjective assessments of potential future cash flows. Third, as mentioned before, there is empirical evidence that contradicts the opinion that self-reported NAVs are generally overvalued. Overall, applying a write-off of 5% to NAVs of all funds that are not beyond their typical liquidation age and one of 30% to NAVs of funds beyond their typical liquidation age appears prudent.

5 Descriptive Statistics and Private Debt Fund Performance

This section provides descriptive and performance statistics for the sample of 347 PD funds analysed. **Table 1** reports descriptive statistics. The sample consists of 117 mezzanine, 54 direct lending, 127 distressed debt, 32 special situations and 17 venture debt funds. Roughly one third of all funds are mezzanine funds and a somewhat larger fraction (37%) consists of distressed debt funds, these two fund types together representing approximately 70% of the sample. The average fund size is USD 950 million (all figures in 2001 US dollars),[109] with distressed debt funds (USD 1,498 million) being the largest and venture debt funds (USD 216 million) the smallest funds, on average. Fund maturity for liquidated funds is 12.6 years, fund maturity for largely liquidated funds is 10.6 years on average.[110] Mezzanine funds have the longest, direct lending funds the shortest maturity.[111] The effective duration of PD funds, however, is much shorter since PD funds distribute cash over the lifetime of a fund. **Table 1** also documents the fraction of funds with an

[109] Fund size is inflation adjusted, based on the Consumer Price Index (CPI) as retrieved from the Bureau of Labor Statistics (BLS), https://beta.bls.gov.

[110] Funds with undistributed assets below 5% are considered liquidated funds, those with less than 50% undistributed assets are considered largely liquidated funds. This is similar in spirit to the approach of Braun et al. (2017), who include funds in which at least 50% oft he capital invested has been realized.

[111] Note that these maturities are largely affected by the fact that direct lending funds, for example, have very late vintage years and are largely unliquidated. Maturity information must therefore be considered with caution.

investment focus on the United States, Europe, Asia or other geographical regions. Clearly, PD funds' geographical investment focus is on the United States with 83.9% of all funds focussing on this region, followed by Europe, with 12.7%, on average. Asia and other regions appear to be of lesser importance with some 3.5% of PD funds investing primarily in these regions. On average, 56% of all PD funds follow a diversified strategy and invest in several unrelated industries. Only 44% focus on one or related industries (such as, for example, health care and pharma).

Additional descriptive statistics are provided in **Table 2**, columns 1 – 5, sorted by vintage year in **Panel B**. The number of funds per vintage year (columns 1 and 2) increases strongly in the pre-GFC period and remains consistently high thereafter.[112] This illustrates the trend for market based financing. Fund maturity (column 3) for fully liquidated funds (vintage 1986 through 1997) / largely liquidated funds (vintage years 1986 through 2003) using a threshold of a maximum of 5% remaining value (RVPI) is 14.3 years / 14.05 years, on average for these vintage years. Allowing for some non-liquidated NAV and extending the observation period from 1986 through 2010, for example, reduces fund maturity to an average 12.8 years. This number is close to the cross-sectional maturity as shown in **Table 1**. Mean fund size is increasing and peaking in 2007, the start of the crisis in the subprime mortgage market. In this vintage year, the 16 funds launched had an average size of approximately USD 1.2 billion (all figures in 2001 dollars), double the size as observed in the cross-section (**Table 1**). Clearly, fund size has increased with the developing PD market. The average fund size prior to the GFC (vintage years 1986 through 2006) is USD 467 million. It increases to approximately USD 641 million in the period including the GFC and the aftermath of it (2007 and vintage years thereafter). The average size decreases somewhat after the GFC (vintages 2009 – 2016) but remains at a high average of approximately USD 571 million. By construction, the remaining net asset value (NAV) scaled by paid-in capital in % ("**RVPI**") is highest for younger, smallest for older and zero for liquidated funds.

[112] The declining number of observed funds in 2016 is due to the fact that PD funds typically start reporting cash flows only after the investment period and not in the fundraising period. The dataset from Preqin is of October 1st, 2018 and does therefore cut-off a number of funds for 2016 that did not yet start their cash-flow-reporting. Interpreting the number of funds launched in the year 2016 to be declining would therefore be misleading.

Performance. Turning to performance in **Table 2,** I report two performance measures and the average performance by vintage year: the internal rate of return (IRR) and the total value over paid-in capital (TVPI) are shown in **Table 2, columns 6 and 7.** The public market equivalent (PME) is shown in **Table 3, columns 6 and 7**. Performance is calculated from LP cash flows using unadjusted self-reported NAVs as in Kaplan and Schoar (2005) on the left hand side of the columns. Additionally, self-reported NAVs are adjussted as described before and resulting in adjusted IRRs, TVPIs and PMEs shown on the right hand side of the columns.

5.1 Internal Rate of Return (IRR)

Kaplan and Schoar (2005), Korteweg and Nagel (2016) or Korteweg and Sorensen (2017) have used this absolute performance measure, which is also widely used by practitioners (Gompers et al., 2016). I use fund cash flows to calculate the IRR. First, an unadjusted IRR is calculated treating self-reported NAVs as market values and including them as if they were distributions to LPs. Formally, the input to this calculation is cash flow data for N funds. For portfolio i (i = 1, ...,N), I observe a series of cash flows between the inception date (denoted t_{0i}) and the end date (denoted T). The cash flows consist of investments from LPs (called “contributions” and denoted “C”) and distributions to LPs (denoted “D”). The IRR of a PD fund i is then calculated as in equation (1):

$$\sum_{t=t_{0i}}^{T} = \left[\frac{D_{it} - C_{it}}{(1 + IRR_i)^{t-t0i}}\right] = 0 \tag{1}$$

Treating NAVs as market values is the approach that has been applied by Kaplan and Schoar (2005) or Harris et al. (2014a), for example. Empirical support for this approach is provided by Robinson and Sensoy (2016) who find that (p. 526): “pre-liquidation NAVs, although self-reported by GPs, are not generally biased estimates of the realized market value of the fund.”

Turning to **Table 2**, treating self-reported NAVs as market values ("$\textbf{IRR}_{\textbf{CF}}$") and aggregating by vintage year, the average (median) performance amounts to 12% (11%). Adjusting self-reported NAVs results in the IRRs depicted on the right-hand side of column 6 ("$\textbf{IRR}_{\textbf{adjusted}}$"). Larger performance differences are only found for younger funds. Their unrealized NAV scaled by paid-in capital (column 5) increases with more recent vintage years and decreases as funds approach liquidation age. On average, the IRR drops by 1% to 11%, whereas the median IRR remains unchanged at a value of 11% when using adjusted NAVs to calculate IRR. It appears that the difference between IRR's is relatively small. The observed IRR of 12% seems high for a debt investment. However, one has to remember that the fund returns comprise multiple elements (cash coupons, payments in kind, upfront fees collected at origination and profits from secondary markets debt transactions).

Panel A of Table 2 shows large performance differences between top-quartile and bottom-quartile PD funds. Top quartile funds show an IRR of 23%, on average, while bottom quartile funds exhibit an IRR of 0%. The large dispersion between top and bottom quartile fund performance seems qualitatively similar for all used performance measures. The average cross-sectional fund performance by fund type is between 8% (for venture debt funds) and 12% (for distressed debt funds).

5.2 Total value over paid-in capital (TVPI)

Next, another commonly used measure of fund performance is used. This is the total value over paid-in capital ("**TVPI**"),[113] net of fees. That is the sum of all cash distributions to a LP plus the remaining value of non-liquidated funds (self-reported NAV), scaled by sum of all cash contributions of a LP. The TVPI of a PD fund i is then calculated as in equation (2).

[113] Some studies call this multiple the «MOIC», meaning the multiple of invested capital. The terms are exchangeable.

$$TVPI = \left[\frac{\Sigma\ Distributions_i}{\Sigma\ Contributions_i}\right] \tag{2}$$

Table 2, column 7, shows this multiple. As before, I first treat the remaining value as a true market value. The calculations and adjustments to self-reported NAVs from the previous section apply and result in a TVPI-multiple calculated myself using LP cash-flows ("**$\mathbf{TVPI_{CF}}$**") and a TVPI-multiple using adjusted remaining values ("**$\mathbf{TVPI_{adjusted}}$**"). Treating self-reported NAVs as market values ("**$\mathbf{TVPI_{CF}}$**") and aggregating by vintage year, the mean (median) performance amounts to 1.54X (1.52X). Adjusting self-reported NAVs results in a mean (median) TVPI multiple depicted on the right-hand side of column 7 ("**$\mathbf{TVPI_{adjusted}}$**") of 1.50X (1.51X). As could be expected and as with the IRR, adjusting the self-reported and undistributed NAVs primarily affects younger funds (later vintage years) but in the cross-section, the adjustment reduces the mean (median) TVPI multiple only slightly from 1.54X to 1.53X (1.52X to 1.51X). Top-quartile funds show a mean multiple of 1.84X, on average, while bottom-quartile funds exhibit a multiple of 1X. The large dispersion between top- and bottom-quartile fund performance seems qualitatively similar to that observed when measuring the IRR of PD funds. Fund performance by fund type is lowest for venture PD funds with a multiple of 1.31X and highest for distressed PD funds with a multiple of 1.43X, on average.

5.3 Public Market Equivalent (PME)

Although practitioners focus much on IRRs and investment multiples, one of the key questions regarding PD is how returns compare with those to public debt. Using timed cash flows, I calculate the public market equivalent ("PME") measure introduced by Kaplan and Schoar (2005) and later used as "the state-of-the-art measure of fund-level performance" (Kaplan & Sensoy, 2015, p. 601) or "the standard performance measure used in the academic literature" (Lerner et al., 2018, p. 17). The PME can be viewed as a market-adjusted multiple of invested capital and is a widely accepted measure in the asset management industry and under the Global Investment

Performance Standards (L'Her, 2016). Rather than absolute performance measures (such as the IRR or the TVPI), the PME adjusts for the market return or the risk of the investments spanned by the benchmark returns and evaluates performance based on cash flows alone. The PME compares an investment in a private debt fund to an investment in a benchmark index. A fund with a PME greater than one outperformed the benchmark index net of all fees over its lifetime. Sorensen and Jagannathan (2013) and Korteweg and Nagel (2013) link PE performance to asset pricing theory and establish that the PME suffices to adjust for risks spanned by the benchmark return, regardless of beta with respect to the benchmark. The assumption is that investors have log utility.

I calculate the present value (PV) of distributions and contributions from the fund level cash-flow data provided by Preqin. The PME compares these PVs from a private debt investment, adjusted for the time value of money. The realized market return (R_{mt}) as given by the benchmark index is used as the discount rate to calculate the PVs. Sorensen and Jagannathan (2014) describe it as the ratio of the present value of distributions scaled by the present value of contributions:

$$PME = \left[\Sigma_t \frac{Distributions_{(t)}}{\prod_{s=toi}^{t}(1+R_{ms})}\right] \Big/ \left[\Sigma_t \frac{Contributions_{(t)}}{\prod_{s=toi}^{t}(1+R_{ms})}\right] \quad (3)$$

The sum runs over the life of the fund from the first cash flows at $s=t_{0i}$ to the time of the distributions or capital calls respectively. As is pointed out by Phalippou (2014), the choice of benchmark is critical to measuring performance. Following the recommendation of Sorensen and Jagannathan (2014) and as practiced in other studies in the PE asset class (see, for example, Harris et al., 2014 or L'Her et al., 2016), I evaluate performance using different benchmark indices. The aim is to find a publicly traded portfolio or index that mimics the return on a typical PD investor's portfolio. Most PE studies use a broad equity index, such as the S&P500, to calculate the PME. Cumming et al. (2019) use the J.P.Morgan Asia Credit Index (JACI) for their PD study focusing on the Asia-Pacific markets. The JACI is a broad index of the public credit markets comprising USD-denominated bonds, invested 76% in investment-grade and 24% in non-investmet-grade debt. An accurate equivalent to these market benchmarks and used in this study are the Bloomberg Barclays indices. They have been the most widely used indices by credit and fixed income investors. An important advantage of these indices is the availability of historical prices that date back to the early vintage years of the PD fund industry.[114] I use two total return indices as benchmarks for the PME calculations. First, the Bloomberg Barclays US Corporate Bond Index.[115,116] It measures the investment grade, fixed-rate taxable corporate bond market and includes USD denominated securities publicly issued by US and non-US industrial, utility and financial issuers. It is also available in local currencies, which are used for PD funds denominated in Euro (EUR) or British Pounds (GBP). Second, corresponding to the notion of tailored PMEs as used in PE analyses (see, for example, Fang et al., 2015; or Robinson and Sensoy, 2016), I use an alternative benchmark: the Bloomberg Barclays US Corporate High Yield Index.[117,118] This index measures the USD denominated, high yield, fixed-rate corporate bond market. I chose these two indices of the public credit market because institutional investors typically compare private market returns with a public index and because these two benchmarks allow a comparison with two indices with different risk profiles.

Panel A of Table 3 shows cross-sectional PME results. The average PME is 1.12 (column 3). This equals an average market outperformance over the lifetime of a fund and using the investment grade benchmark of 12%. Using the high yield benchmark in column 4, the cross-sectional PME is reduced to 1.07 (7%). Splitting the sample into PME performance quartiles, the

[114] This is not the case for the S&P Global Bond index family, for example, for which corporate credit or fixed income indices have only been introduced in 1993 and later. Also, a potentially suitable benchmark, the S&P/LSTA Leveraged Loan Index (LL100), as used in Munday et al. (2008) dates back only to 2002.

[115] US Corporate Baa TR Index: Bloomberg ticker “LCB1TRUU”

[116] Daily index prices are available from December 24, 2003. From September 1, 1988, only monthly index values are available on Bloomberg and daily index prices are estimated using linear interpolation.

[117] US Corporate High Yield: Bloomberg ticker “LF98TRUU”. Securities are classified as high yield if the middle rating of Moody's, Fitch and S&P is Ba1/BB+/BB+ or below.

[118] Daily index prices are available from July 31, 1998. Prior to this date, only monthly index values are available on Bloomberg. Daily prices before this date are estimated using linear interpolation.

top funds outperform the investment grade benchmark by a mean (median) of 44% (34%). Over their lifetime, bottom quartile funds underperform the market by a mean (median) of 16% (11%). The cross-sectional PME varies largely by fund type: At the lower end, a mean market outperformance of 6% for venture debt funds is observed, compared to an outperformance of 15% for distressed debt funds at the higher end. **Figure 3** graphs kernel densities of PMEs for the five fund types analysed as well as for the cross-section of all funds. Direct lending fund PMEs appear to be less dispersed than those of other fund types. The cross-sectional PME for direct lending funds has a standard deviation (sd) of 0.11, followed by venture debt funds (sd = 0.16), mezzanine funds and special situation funds, each with a sd of 0.29, and distressed debt funds (sd = 0.34). Clearly, fund performance as measured is fat tailed and right skewed, on average.

Panel B, columns 3 and 4 of Table 3 show the PME as calculated with the investment grade benchmark (high yield benchmark), sorted by vintage year. Both columns show the mean and median PME determined with unadjusted cash flows on the left side (PME_{CF}) and using adjusted cash flows ($PME_{adjusted}$) on the right side. Aggregated by vintage year, the mean unadjusted (adjusted) and equal-weighted PMEs over the sample period are 1.17 (1.18). The median unadjusted (adjusted) PMEs amount to 1.16 (1.14). This indicates that over their lifetime, PD funds outperform the investment grade benchmark by an unadjusted (adjusted) average 17% (18%), the difference from the NAV-adjustments amounting to 1%.

Kaplan and Schoar (2005) use the term cumulative alpha for the performance in excess of a PME of 1. In their terminology, a PME of 1.2 is equivalent to a cumulative alpha of 20%, created over the life of a fund. I a comparable vein, I calculate the annualized alpha (α) from the cumulative alphas. The days of each fund's life from the first to the last reported cash flow (or last reported NAV) are counted and divided by 365 to calculate the investment periods measured in calendar years (y_i). For each fund, alpha is then approximated by $(PME_i)^{(1/y_i)} - 1$. **Columns 6 and 7 of Panels A and B** show the annualized alpha as calculated from the PME. Using the investment grade (high yield) benchmark and sorted by vintage year, alpha amounts to 2% (1%) in the cross-section. The large performance dispersion between top- and bottom performance funds is reflected in likewise large differences in annualized alpha. Measured with the investment grade (high yield) benchmark, top funds provide an alpha of 5.96% (4.88%), while bottom funds provide an alpha of -2.57% (-3.23%).

As can be seen in **Panel B of Table 3**, alphas show large time variation if sorted by vintage years. The data suggests that alphas vary strongly in the period prior to the Global Financial Crisis (GFC), whereas they become more stable and remain consistently positive in the post-GFC period. I therefore compare the cross-sectional alpha for the pre- and post-2008 period: alpha as calculated from the investment grade benchmark has increased more than sixfold in the post-2008 period, on average, and increased from 0.46% to 2.87%. Likewise, alpha as calculated from the high yield benchmark is close to zero (-0.02) for the period pre-2008, on average. Thereafter it increases to 1.61%.

5.4 Risk and Abnormal Performance of PD funds

It has been shown above that PD funds outperform the market as measured by the PME_{IG} (PME_{HY}) by 17% (12%), on average, and by 44% (35%) in the cross-section of top quartile funds. This outperformance is calculated from the PME as in Kaplan and Schoar (2005) and adjusts for risks spanned by the benchmark returns, regardless of beta and under the assumption that investors have log utility.[119] However, investors may not have log utility and it is likely that there exist risks associated with PD funds that are not spanned by the two benchmarks. It therefore appears accurate to decompose PD fund returns by estimating the beta (and alpha) for the cross-section of PD funds.

Driessen et al. (2012) provide a methodology to estimate risk and return of nontraded assets from cash flows. They minimize the sum of squared differences between the present value of fund distributions and contributions using a stochastic discount factor (SDF) calculated from the risk-free rate (R_f) plus the estimated alpha (α) plus the realized excess market return (R_m-R_f) times beta (β). In their methodology, the standard IRR calculation is extended by incorporating

[119] See Sorensen and Jagannathan (2013) and Korteweg and Nagel (2013) for a formal justification.

exposure to realized market returns. Using a discount rate that is different in each period and equal to $1 + R_f + \alpha + \beta(R_m\text{-}R_f)$, this can be expressed as in equation (4):

$$\text{NPV}_i(\alpha,\beta) = \left[\Sigma_t \frac{\text{Distributions}_{(t)}}{\prod_{s=toi}^{t}((1+ R_{fs} + \alpha + \beta(R_{ms}\text{-}R_{fs})\ \ )}\right] - \left[\Sigma_t \frac{\text{Contributions}_{(t)}}{\prod_{s=toi}^{t}((1+ R_{fs} + \alpha + \beta(R_{ms}\text{-}R_{fs})\ \ )}\right] \quad (4)$$

As in Driessen et al. (2012), Section IV.C, I use portfolios grouped by vintage year to eliminate small sample biases. This yields 28 value weighted portfolios sorted by vintage year and thus 28 moment conditions. Quarterly cash flows for the period 1986 through 2016 are used to calculate the present values of portfolio i. The realized market returns (R_m) are employed when discounting cash flows (and not expected returns). The USD 1-year treasury constant maturity rate is used as the risk-free rate (R_f). As above, the Bloomberg Barclays US Corporate Bond Index (IG) and the Bloomberg Barclays US Corporate High Yield Index (HY) are used as market return (R_m) and serve to estimate abnormal performance (α) and risk loadings (β) within a one-factor market model. Additionally, I use the the value-weighted index of all US stocks compiled by the Center for Research in Security Prices (CRSP).[120] Using the stochastic discount factor (SDF) as in equation (4), I estimate α and β so as they most closely force all fund NPVs equal to zero. **Table 4** shows the alphas and betas using the methodology as in Driessen et al. (2012) for the three benchmarks.

Starting with the investment grade benchmark in Panel A, PD funds have a quarterly (annualized) alpha of 2.46% (10.21%), significant at the 1% level. Beta amounts to -0.13 and is statistically not significant. Turning to the high-yield (HY) benchmark in Panel B, PD funds have a quarterly (annualized) alpha of 2.19% (9.05%), significant at the 1% level and an insignificant beta of 0.05. Benchmarking PD fund cash flows against US stocks in Panel C, I find a quarterly (annualized) alpha of 1.62% (6.64%), significant at the 1% level. The beta of 0.43 is now significant at the 5% level.

[120] Data on CRSP indices are from CRSP, accessed via http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

This analysis suggests that PD fund returns resemble, if anything, those of US stock returns. The t-value for the beta using the stock return benchmark is 2.19 as compared to those of the IG- and HY-benchmarks, which are -0.39 and 0.15 respectively. Given these betas, PD funds may be considered market neutral with respect to bond markets and, with a significant beta of 0.4, moderately related to equity markets. It appears that PD fund returns are not significantly affected by the bond benchmarks. If it holds that beta is zero, then alpha is essentially the expected return in excess of the risk-free rate. Taking the cross-sectional (over the sample period) risk-free rate of 3.59% as a naïve estimate and using these alphas, the expected returns for PD funds as estimated from Panels A and B are 13.80% (3.59% + 10.21%), 12.64% (3.59% + 9.05%). Taking a naive estimate for the equity premium of approximately 4.5% (assuming an average long-term equity market return of 8%) and the same risk-free rate, the cost of capital is 3.59% + 0.43 X 4.5% = 5.5%. Using the significant abnormal positive return (α) of 6.64%, this results in an approximate IRR of 5.5% + 6.6% = 12.1%, according to the CAPM.

One could expect that the cross-sectional static IRR is close to this expected return calculated from a time-varying discount rate. Comparing the previously calculated static IRR of 10.6% to the expected returns using the bond benchmarks, however, the difference is between 2% (Panel B) and 3.2% (Panel A).

The estimated risk and abnormal performance characteristics of PD funds shown in Table 4 provide several insights. First, the data suggests that PD fund returns are largely unsystematic or market neutral when compared to bond and moderately systematic when compared to equity markets, indicating diversification benefits. Second, although the significance being indistinguishable from zero for the bond benchmarks, betas appear to be reliably different from one. This observation is in line with Munday et al. (2018), who find relatively low betas. The results presented before in Section 5.3 using the Kaplan and Schoar (2005) public market equivalent (PME) and assuming a beta of one, may therefore be downward biased in terms of alpha and understate the true risk-adjusted returns (α's) to bond markets. Third, it appears that PD funds constitute an asset class that is largely independent of bond markets. Finally, as PD fund performance is not largely explained by the return on the market portfolio as mimicked by the used benchmark indices (β), it appears that, on average, there is high alpha in this asset class, suggesting that PD funds add value.[121]

5.5 Performance of first-time and one-time PD funds

In this Section I control for the performance effects of first generation funds and one-time funds. First-time funds are those funds for which data have entered the Preqin PD database for the first time. At least one or more funds then follow these first-time funds, managed by the same GP. First-time funds differ from one-time funds. The latter are funds that enter the sample once but for which no subsequent fund managed by the same GP is observed in the dataset. Little is known about the extent of attrition among GPs focused on PD funds. However, I find that a substantial 78 in 160 first-time GPs do not have a second PD fund in the database. This fact can be related to GPs simply ceasing to report their performance to Preqin. Alternatively, their disappearance, or attrition, can be rooted in their bad performance. If so, a conditioned subsample should evidence that one-time funds have a performance which is worse than that of other funds. **Table 5** compares the performance measures used in the previous sections (IRR, TVPI, PME and annualized α for the unconditioned cross-section (column A) and as a baseline, to one-time PD funds (column B), first-time funds followed by successive funds (column C), the cross-section without one-time PD funds (column D) and the difference between columns D and A as an indication of potential effects from attrition.

Compared to the baseline, one-time fund performance (column B) is substantially worse for all performance measures, the difference always statistically significant at the 1%-level. One-time funds appear to add little or no value to investors when using annualized alphas. They underperform the high-yield benchmark by an approximate -0.3% per annum and barely keep up with the investment-grade benchmark. Also, their IRR (TVPI multiple) is reduced from the cross-

[121] Assessing value creation is typically measured by abnormal returns gross of fees. However, if α is positive after fees, as calculated in this paper, it gets only better before fees.

sectional baseline result of 10.6% (1.4) to a lower 6.7% (1.2). Turning to first-time funds with follow-on funds managed by the same GP (column C), they appear to perform substantially better than those funds that are not first-time funds. Comparing their performance to one-time funds (column B), all performance measures are better for the first-time funds. When comparing the cross-sectional performance of the sub-sample that does not include one-time funds (column D) to the baseline results (column A), performance is better for all performance metrics. This comparison shows a potential survivorship bias in the PD fund data. Related to the IRR, TVPI-multiple, PME_{IG} and PME_{HY} as well as annualized alphas for IG and HY, the potential survivorship bias accounts for (column E) approximately 1.1%, 0.05X, 3% and 3% as well as 0.31% and 0.37%. The data therefore suggests that attrition affects the performance data of PD fund samples. The magnitude is approximately comparable to that observed in longer term mutual fund samples (Carhart et al., 2002). It appears that accounting for PD fund survivorship, the average performance as depicted in Tables 2 and 3 increases. However, these results should be interpreted with caution and do not necessarily represent the PD fund population as funds might disappear from the Preqin database for reasons other than low performance. Also, I can only identify one-time funds with high accuracy for the early vintages in my sample. For more recent vintages it is unclear whether a fund is a one-time fund or one that will later be followed by a successive fund and consequently be classified as first-time fund. More comprehensive studies focusing solely on the question of PD fund survivorship biases are needed to understand better, how survivorship biases affect PD fund performance.

6 Performance Persistence

Can past performance help investors to make performance predictions? This question is considered next. I employ three analyses to evaluate whether performance of a given fund, as measured by PME, is associated positively with the performance of the next fund managed by the same GP. First, current performance is related to past performance running cross-sectional linear OLS regressions. This approach has been applied in the seminal work of Kaplan and Schoar (2005), in more recent studies (for example Braun et al., 2017) and in Harris et al. (2014b). According to Kaplan and Sensoy (2015), Harris et al. (2014b) conduct the most comprehensive analysis of fund-level performance persistence in PE.

Second, I consider persistence by performance quartile and calculate Markov transition probabilities from one performance quartile into the same or another performance quartile by funds managed by the same PD firm. In a third analysis, which is presented in Section 7 separately, I control for other factors that potentially affect fund performance and persistence.

6.1 Regressing current fund performance on past performance

First, current fund performance is related to past performance. Of the 347 funds in the sample, 184 have performance data of a partnership's previous fund.[122] While it would be preferred to have no gap in the fund sequence, the sample is considerably larger than that of Kaplan and Schoar (2005), who analyze persistence of buyout fund performance based on only 76 funds with prior performance history, or that of Robinson and Sensoy (2016), who measure performance persistence based on 73 venture capital fund sequences. It is, however, comparable to the 152 buyout funds with prior performance that Robinson and Sensoy (2016) use to estimate persistence and to the 179/193 funds with prior performance that Harris et al. (2014a) have in their sample to analyze persistence of buyout/venture capital funds in the period post 2000.

Panel A of Table 6 shows ordinary least squares (OLS) regressions of current PME_{IGit} and PME_{HYit} on the lagged PME_{IGit-1} and PME_{HYit-1}. Since the number of PD funds has markedly picked up just prior to the Global Financial Crisis (GFC), I run the regressions for three periods: for the whole sample period (columns 1 and 4), for the pre-GFC period (columns 2 and 5) and for the post GFC-period (columns 3 and 6), that is for all vintages as well as the pre- and post-2007 vintage funds.[123] Given that PME is right skewed, I estimate regressions using log PME (for both current

[122] For the high yield (HY) benchmark index three additional observations are available since index data dates back longer than that of the IG benchmark.

[123] The post-2007 period includes also vintage year 2007.

and previous PME). To gauge for the effect of vintage years and the impact of vintage year specific economic and market conditions, I include vintage year fixed effects as indicated. As shown in **Table 3**, there is large variation in performance across the different fund types. I therefore control for the average differences across fund types and include fund type dummy variables.

As shown in **Panel A of Table 6**, for the whole sample period, previous performance as measured by the log of PME_{t-1} is significantly related to current fund performance (log of PME_t). A 10% increase in the lagged performance using the investment grade benchmark (high yield benchmark) is associated with a 1.7% increase in the log of current fund performance. Using the cross-sectional PME of 1.12, for example, a 10% increase in previous performance is associated with an improvement in market outperformance from 12% to 13.8%.[124] For funds with vintages in the pre-2007 period, persistence in PD fund performance disappears and is statistically not different from zero. The opposite is observed for funds launched in or after vintage year 2007. Persistence for these funds is highly statistically significant: a 10% increase in prior fund performance predicts an increase in the log of PME_t by 2.3% to 2.4% (columns 3 and 6) or an increase in average market outperformance from 12% to approximately 14.6%.[125]

Given that performance for top-quartile funds is considerably higher than that for bottom quartile funds (see **Table 3**), I next analyse whether persistence for those funds with a prior fund that has outperformed the market (i.e. PME >=1) is different from that of funds with a prior fund that has underperformed the market (i.e. PME <1). Underperforming funds represent the 4th quartile, while outperforming funds represent the top and the 2nd quartile primarily. **Panel B of Table 6**, shows ordinary least squares (OLS) regressions of current PME_{IGit} on the lagged positive $PME_{IGit-1(+)}$ and negative $PME_{IGit-1(-)}$. Vintage year fixed effects are used in all regressions. No funds with negative previous PME are observed for the pre-2007 period and column 4 is therefore

[124] As the ln(1.1) = 0.095, the expected log outperformance is 0.095*0.171 = 0.016 in the next period, leading to a PME of exp(0.016) = 1.016. Given the average PME of 1.12 this leads to a PME of 1.0163*1.12 = 1.138.

[125] Same calculation as in footnote 27, but multiplying the log outperformance by 0.238 (= 0.234 + 0.243 / 2).

empty. The results suggest that persistence is driven by outperforming funds of the post-2007 period. Performance persistence for these funds is statistically significant at the 1% level. Contrary to this, persistence for underperforming funds is not significant for the same sub-period. Positive prior outperformance appears to be a statistically significant predictor of current performance for the post-2007 period, while underperformance does not predict low performance of a subsequent fund. For the post-2007 period, a 10% increase in the previous funds PME of outperforming funds is associated with a 3% increase in the current fund log PME or an increase in average market outperformance from 12% to approximately 15.3%.[126] The results are qualitatively similar when using the HY-benchmark.

6.2 Quartile transition probabilities

Next, as in Kaplan and Schoar (2005) or Harris et al. (2014b), [127] I consider whether previous fund quartile performance, as measured by PME, is informative of current performance calculating conditional transitions probabilities. Each previous fund is grouped into the top-, 2nd, 3rd or bottom-quartile. Current funds with past performance quartile information are then also grouped into the top-, 2nd, 3rd or bottom-quartile. **Table 7, Panel A,** reports the crosstabs per PME quartile for the whole sample. These show the probability that a partnership's next fund wll either stay in the same performance quartile, or move into one of the other three quartiles. PD funds with a previous fund in the top-quartile are in the top-quartile in 39.1% of all cases. Likewise, funds with prior bottom-quartile performance remain in the bottom quartile in 37.0%. This finding indicates very high performance persistence in general and at both ends of the distribution. Top-quartile to 3rd quartile (bottom quartile) transitions are observed in 21.7% (15.2%) of all cases and

[126] As the ln(1.1) = 0.095, the expected log outperformance is 0.095*0.302 = 0.029 in the next period, leading to a PME of exp(0.029) = 1.029. Given the average PME of 1.12 this leads to a PME of 1.029*1.12 = 1.1527 or an outperformance of 15.3%.

[127] Kaplan and Schoar (2005) use terciles, instead of quartiles. Methodologically the categorization into performance groups is identical.

the inverse, bottom-quartile to second (top quartile) transitions are observed in 23.9% (13.0%). Selecting PD funds with previous top-quartile performance in Panel A, for example, yields an expected performance of the follow on fund managed by the same GP of $E(\text{PME}_{\text{IG}}|\text{PQ}) = 1.2$.[128] Panel D includes a naïve model predicting the expected return from given previous quartile performances and the observed probability distribution of funds staying in the same or switching into another performance quartile. Overly simplified, this naïve model must be extended by the findings from a more complete model presented in the next Section.

Next, the analysis is repeated for the pre- and post-2007 periods. The results are presented in **panels B and C of Table 7**. While the persistence remains high in both periods, it is much higher in the post-2007 period, especially for the top-quartile. PD funds with a previous fund in the top-quartile are expected to remain in the top-quartile in 50% of all cases in the post-2007 period. Likewise, funds with prior bottom-quartile performance remain in the bottom quartile in 41.7% of all cases. For the pre-2007 period, persistence for the top-quartile is lower and amounts to 30%. Also, the expectation of remaining in the bottom-quartile if a previous fund was a bottom-quartile fund is slightly lower and amounts to 40%. It appears that persistence in the post-2007 period is very high in general and at both ends of the distribution. Persistence in PD fund performance as compared to that of PE funds is sizeable. For example, Harris et al. (2014b)[129] find a persistence of 27.5% for PE funds remaining in the top-quartile.

Overall, it appears that investors can improve their choice of funds by using quartile transition probabilities. The results from the OLS regressions (**Table 6**) and the quartile transition probabilities (**Table 7**) are consistent at the high end of the performance distribution. Positive previous performance is related to positive current performance. In both analyses, persistence is driven by post-2007 observations. For funds launched prior to 2007, persistence appears to be lower. These results deviate from persistence observations in the PE fund universe. Harris et al.

[128] The expected average PME_{IG} of the follow-on fund given previous quartile information [$E(\text{PME}_{\text{IG}}|\text{PQ})$] of 1.2 is calculated from the probability of staying in a specific quartile, multiplied by the observed performance of this quartile, i.e.: (0.39 X 1.44 + 0.24 X 1.15 + 0.22 X 1.06 + 0.15 X 0.84).

[129] Kaplan and Schoar (2005) use terciles for a somewhat smaller sample and find a 55% chance of staying in the top tercile using PME as performance measure.

(2014b), for example, document persistence in PE in pre-2000 funds. After 2000, they find little evidence of persistence for buyout funds. Likewise, Braun et al. (2017) find declining persistence over time and little evidence of persistence in investments made since the late 1990s. Contrasting these results for PE, PD fund persistence in performance has raised over time: I find significant persistence in post-2007 funds. Pre-2007, I find little evidence of persistence.

7 Other Factors Affecting PD Fund Performance & Persistence

This Section analyses other factors that may influence performance and persistence. Motivated by prior research investigating PE fund performance as reviewed by Kaplan and Sensoy (2015) and Korteweg (2018) and the PD related study of Cumming et al. (2019), I include additional factors that might affect PD fund performance. I differentiate between fund specific factors, such as fund type, focus and size on the one side and economic factors, such as funding liquidity, recessionary periods and the amount of aggregate capital flowing into the PD fund asset class on the other side. Paragraphs 7.1 through 7.8 define the used independent variables and show the results of simple linear regressions in **Table 9** employing these variables. A multiple linear regression approach is used in paragraph 7.9. The results are shown in **Table 10**.

Returns can not be observed on a regular basis and cash flows are highly skewed. I therefore use the log of performance on the independent variables that represent either the average level or the average change of an independent variable for the vintage year (t) and the following calendar year (t+1). The variables are assumed to be exogenously determined. Estimating performance from observations of years t and t+1 solely, the following analyses are based on somehow noisy measures. Factors relevant in periods other than year t and t+1 may influence ultimate fund performance. However, the approach is in line with Kaplan and Strömberg (2009), who use this approach to analyse the relation between capital commitments to US PE funds and their later returns. The following analyses adopt the regression approach as used in Kaplan and Strömberg (2009). Given the methodological approach, it is suggested that the regression results presented below are considered illustrative of broader patterns.

7.1 Fund type

First, fund type variables are considered. Preqin provides PD fund type grouping differentiating between different investment strategies (mezzanine, direct lending, special situations, distressed and venture debt funds). Although not mutually exclusive, a fund's investment strategy most likely affects a fund's performance and persistence in performance. To analyse this, previous fund performance PME_{it-1} is interacted with the five fund types grouped by Preqin. Fund type dummy variables are added to account for the large dispersion of performance across the different investment strategies. **Table 8** shows how persistence varies by fund type using the investment grade (columns 1 through 3) and the high yield benchmark (columns 4 through 6). For special situations funds, no previous fund information is available in the pre-2007 period. The data suggests there is significant persistence for direct lending funds, special situations and distressed debt funds for the post-2007 period and using both benchmark indices.

7.2 Focus

Gompers et al. (2009) find that venture capital (VC) partner specialization can explain cross-sectional differences in performance. According to their study, increased specialization of VC firms is associated with greater average success. The poorest performance they find is for unspecialized firms that follow a generalist investment approach. Gompers et al. (2009) relate their result to industry-specific human capital and specialization of partners. In this vein, Ewens and Rhodes-Kropf (2015) observe that GP partners' human capital is important in explaining VC firm performance. Cumming et al. (2019) find that manager experience is positively associated with PD fund returns, suggesting learning effects from investing in PD markets. Since human capital is limited, it appears to be an empirical question whether focus facilitates specialization and learning, affecting PD fund performance and its persistence. As is shown in **Table 1**, PD funds focus their activities in at least two dimensions beyond their investment strategy as indicated by fund type. First, they focus geographically. Second, they focus on one or more industries and thus follow a diversified or non-diversified investment strategy in that respect. Approximately 84% of all funds have their primary investment focus in the US market, the remaining regions being Europe (12.7%), Asia (2.9%) and other regions (0.6%) or together 16.1%. This may reflect the relatively low reliance of US borrowers on the banking sector.[130] Overall, approximately 56% of PD funds follow a diversified investment strategy, that is they invest in several and unrelated industries. Whereas geographical focus is mostly on the US for all fund types, industry focus differs from type to type. Mezzanine funds, for example, appear to be very focused with 63.3% investing in only one or related industries, whereas direct lending funds are generally diversified with only 35.2% investing in only one or related industries and 64.8% of capital being allocated to multiple and unrelated industries. The impact of geographical focus is measured by a dummy variable in **column 1 of Table 9.** The dummy variable takes the value of one if a fund is focused on the US market, zero if focused towards Europe, Asia or other regions. I find no significant relationship between geographical focus and PD fund performance. Turning to " industry focus" in **column 2**, it appears to be unrelated to fund performance. Given the simple regression results, focus appears to be unrelated to PD fund performance. However, in view of the findings of Gompers et al. (2009), Ewens and Rhodes-Kropf (2015) or Cumming et al. (2019), the statistical evidence might at this point of the study be insufficient to suggest that PD fund performance is in effect unrelated to industry focus. I will control for this when using the multiple regression approach in the next section.

[130] According to the latest Global Shadow Banking Monitoring Report, the US accounts for approximately 31% of global shadow banking assets (held by non-banks), followed by Europe with a total of 22%. See exhibit 4-5, p.50 Financial Stability Board (2018). In the US, non-bank credit is larger than the size of bank credit, whereas in Europe, firms largely rely on bank credit. As can be taken from the BIS (www.bis.org/statistics/totcredit.htm), the market share of total credit to non-financial corporations as a percentage of GDP by banks relative to total credit to non-financial corporations in the US was approximately 34.4 % in 2017. This compares to a more bank reliant system in Europe (G20 aggregate) with a relative market share of banks of 54.8% (58.4%).

7.3 Size

As shown in **Table 2**, fund size has, on average, increased substantially over time. The average fund size (measured in 2001 dollars) has experienced a more than tenfold increase from approximately USD 160 million for the 1986 vintage to later vintages just prior and during the GFC in 2007 and onwards. As has been shown in PE studies, the relationship between fund size and performance may vary across different fund types. Kaplan and Schoar (2005), Harris et al. (2014a) and Lopez-de-Silanes et al. (2014), for example, find no statistically significant relationship between size and performance for buyout funds. Harris et al. (2014a), however, find that performance of venture capital funds is negatively related to fund size. In Harris et al. (2014b), the analysis of this variable provides mixed results. Cumming et al. (2019) find a marginally significant effect of size on performance using a sample of private debt transactions. To control for a potential effect of size, I use the log of fund size (in 2001 US dollars)[131] in **column 3 of Table 9**. The result suggests that fund size is negatively related to performance.

7.4 Capital raised

Kaplan and Strömberg (2009) and Harris et al. (2014a) observe and suggest that PE fund performance is significantly negatively related to capital commitments. To test this for PD funds, I use the historical private debt fundraising data from Preqin and verify how aggregate capital inflow into the PD asset class may affect fund performance. One may assume that more capital inflow into the PD industry may increase competition amongst PD funds for investment projects, lowering project returns. Kaplan and Strömberg (2009) find that inflows of capital in the vintage phase can explain realized fund returns during the subsequent ten- to twelve-year period. As PD funds typically draw down committed capital in the first two years of their life, I use the total

[131] In unreported tables, I also control for the change of fund size from the previous to the current fund, which is measured as the log of change in fund size. Additionally, I use size measured in non-inflation adjusted US dollars. The result remain unchanged.

aggregate amount raised in the vintage year (t) and one year thereafter (t+1) to measure aggregate capital inflow into the PD industry. The log of PME_{it} is then regressed on capital raised as an additional independent variable. Preqin provides information related to aggregate raised capital per vintage year only from the year 2000 onwards, which reduces the sample size marginally to 171 observations. The result in **Table 9, column 4** suggests that PD fund performance is not related to the aggregate capital inflow into the PD industry.

This result contrasts the finding of Kaplan and Strömberg (2009) or Harris et al. (2014a), who find that performance is negatively related to capital commitments. However, the t-value of 1.63 indicates a relationship between capital commitments and performance, this relationship to be explored in more detail in the multiple regression approach in the next section.

7.5 Credit standards (SLOS)

A different broad pattern that is related to liquidity and reflects debt market conditions is the change in credit standards as reported in the Federal Reserve's Senior Loan Officer Survey.[132] The change of credit standards, according to Axelson et al. (2013, p. 2257) "captures nonprice aspects of credit market conditions, such as debt covenants and quantitiy constraints.". They find that this measure is strongly related to the amount of leverage used in the PE industry. Franzoni et al. (2012) proxy funding liquidity by SLOS and define it as a positive (negative) percentage change of loan officers tightening (loosening) their credit standards. When including SLOS together with market liquidity into their regressions, they observe that SLOS absorb half of the market liquidity effect and impact cash flows to LPs, which are reduced when credit standards are tightened. Motivated by the results of Axelson et al. (2013) and Franzoni et al. (2012), I expect that tight (loose) credit standards are related to PD fund performance. I include two dummy variables indicating the state of SLOS at the extreme deciles. The average SLOS tightening (loosening) of the vintage year (t) plus the following calendar year (t+1) are used as independent

[132] Data are from the Federal Reserve, https://www.federalreserve.gov/data/sloos/sloos-201810-chart-data.htm

variable. “Credit standards loose” takes the value of one if changes in Senior Loan Officer Standards (SLOS) are at the extreme left hand side of the distribution, that is at the 10th percentile. This state indicates very loose SLOS. ”Credit standards tight” takes the value of one if changes in SLOS are at the extreme right hand side of the distribution, that is the 90th percentile, indicating very tight SLOS. Column **5 of Table 9** shows the result. Loose credit standards are negatively related to PD fund performance and reduce it by a marginally significant 6.4%.[133] On the contrary, no statistically significant relation between very thight credit standards and performance is observed. Roberts and Sufi (2009) have shown that the terms of the initial lending contract play an important role in renegotiation as it is partially controlled by the contractual assignment of bargaining power. As is the case in the PE context (Axelson et al., 2013), loose credit standards might be a proxy for lower covenant protection and fewer quantity constraints, both affecting a PD fund’s performance negatively. The data suggests comparable mechanisms are at play also in the PD industry.

7.6 Funding Liquidity (TED spread)

Investors require higher or lower discount rates in compensation for higher or lower liquidity of an asset.[134] Given that LPs commit to PD funds for a long time period, it is possible that there is a large liquidity risk premium. Controlling for liquidity therefore appears to be informative when evaluating PD fund performance and its persistence. Since PD funds are illiquid per se, that is they can generally not be traded without consent of the GP, it is difficult to proxy for the required illiquidity premium requested by investors. For the PE industry, Nadauld et al. (2018) show that LPs who sell their PE fund stakes in the secondary market accept discounts of

[133] Remember that the dependent variable is log-transformed and the dummy variable “credit standards_loose” is in its original metric. To interpet the amount of change in the original metric of the outcome, here the log of PME, I exponentiate the coefficient of census to obtain exp(-0.0623) = 1.0642. Subtracting one from this number and multiplying it by 100 results in the percentage change of 6.4%.

[134] Different types of liquidity exist. The large and growing literature is described in a comprehensive way in Dimitri and Jiang (2013) . In this paper, I focus on concepts of liquidity that have been used in prior PE or PD research.

approximately 9%, fluctuating with fund age and market conditions. This explanation appears to be unlikely to explain large fractions of performance of PD funds, however. Given the underlying assets, PD funds should be less risky than PE funds and the discounts observed by Nadauld et al. (2018) for PE funds should be smaller when analysing PD funds. Systemic liquidity of the market as a whole might be related to performance and explain parts of the PME. I therefore control whether PD fund performance, like that of other asset classes, is affected by market liquidity. Brunnermeier and Pedersen (2009) find that in times of market illiquidity, funding liquidity also dries up. Cumming et al. (2019) apply this concept and use funding liquidity as proxied by changes in the TED spread. They suggests that an increase in TED spread (worsening funding liquidity) is positively related to the outperformance of a PD loan portfolio versus the market. Their explanation is that secondary market price discounts increase with shrinking liquidity, thereby increasing the returns to debt investors. In fact, they find the supposed positive relationship between funding liquidity and performance.

TED spread is the difference between the three-month LIBOR and the three-month T-bill rate as calculated by the Federal Reserve Bank of St. Louis. I control for funding liquidity using the log of the average level of TED spread for the vintage year (t) and the consecutive year (t+1), which in my view approximates funding liquidity in the market. PD funds usually allocate the capital called from LPs in the first and the second year of a fund's lifetime. Data are from Bloomberg and TED spread is measured in basis points.[135] **Table 9, column 6** shows the result. Funding liquidity proxied by TED spread is negatively and significantly related to performance. A 10% increase in TED spread (worsening funding liquidity) decreases performance by 0.8%, the coefficient being significant at the 5% level.[136] This result contrasts with the finding of Cumming

[135] TED spread is only available on Bloomberg from January 2nd, 2001 onwards. However, the rate on interbank loans (LIBOR) and short-term US government debt are available. I therefore replicate the spread using these two rates as available with the Bloomberg tickers US0003M / USGG3M.

[136] To make this result comparable to the study of Cumming et al. (2019), I also use the average change in the TED spread of the vintage year compared to t-1 plus the change of the TED spread of the consecutive year compared to that of the vintage year. Using the log of change in TED spread instead of the level of TED spread renders a coefficient that is approximately half in size and significant at a lower 10% level.

et al. (2019). A potential explanation for the negative sing is that PD funds may find it difficult to refinance their investments in times of low funding liquidity and be confronted with higher borrowing costs, translating into lower returns to PD funds.

7.7 Recession

Adverse economic conditions may impact PD fund performance independent of funding liquidity or capital inflows. I therefore control for the effects of US business cycle expansions and contractions. Data are from The National Bureau of Economic Research (NBER) and used to identify vintage years that fall together with times of recession. A recession dummy variable ("recession") is used. It takes the value of one if a PD fund vintage year is equal to a recession year as reported by the NBER. This includes vintage years 1990, 1991, 2001, 2008 and 2009.[137] Default rates tend to be higher during recessions, recovery rates are typically below their long-run means and spreads increase (Duffie & Singleton, 1999; Chen, 2010). This may affect PD fund performance in many ways. For example, it may lead firms to manage their leverage ratios counter cyclically, making it harder to PD funds to find attractive investment opportunities during recessions (Hackbarth , 2006). Also, it may make it harder to PD funds to restructure debt positions as recovery rates typically decrease and loss given defaults increase respectively in recessions (Acharya et al., 2007; Jankowitsch, 2014). As a consequence, PD fund performance of funds raised in recessionary periods may be negatively affected. These explanations appear to be unlikely given the empirical results shown in **Table 9, column 7**. PD fund performance of funds raised during the recession of 1990/91 or the internet bubble (2001) period is positively related to performance. The performance estimation for funds raised in these times indicates an economically important and significant difference compared to funds raised outside recessionary periods of 35.9% (33.5%). Interestingly, the global financial crisis (GFC) dummy variable is not

[137] I do also control for the effect of including the year 2002 as a recession year since the Nasdaq Composite stock market index peaked in March 2000 before crashing, with a burst of the bubble (dot-com crash) until October, 2002. Results are not materially affected by this.

significant. It appears that the early recessions offered attractive investment opportunities to PD funds. These might have been affected by the bank lending channel drying out in recessions (for example based on credit rationing as described in Stiglitz & Weiss, 1981) or by banks seeking to de-risk their balance sheets and protect bank equity (Acharya, et al., 2016; Acharya et al., 2015) in recessions. Lemmon and Roberts (2010), Duchin et al. (2010) and Carvalho et al. (2016) show that substitution to alternative sources of capital given contraction in the supply of credit is limited. While short-term loan-to-bond substitution may help large corporates to compensate for decreasing bank credit supply in crisis periods (Adrian, Colla, & Shin, 2013; De Fiore & Uhlig, 2015), firms without direct access to public markets may therefore find it difficult to use alternative financing channels and want to borrow from more flexible PD funds. A contraction in the supply of bank credit may therefore lead to attractive investment opportunities and increase PD fund performance.

7.8 Credit spread

Finally, I also control for the pricing of global risk using credit spread as in Cumming et al. (2019). I hypothesize that market outperformance as measured by PME is positively related to credit spread, as investors require higher discount rates in compensation for higher global risk. Credit spread is the average yield spread between Moody's Seasoned Baa Corporate Bond Yield relative to the 10year Treasury constant maturity yield, of the vintage year (t) and the following year (t+1). Data from the Federal Reserve of St. Louis. As is shown in **column 8 of Table 9**, it is positively related to PD fund performance. A one standard deviation increase in spread (sd = 0.55) increases fund performance by approximately 4%.[138]

[138] The dependent variable is log-transformed and credit spread is in its original metric. To interpet the amount of change in the original metric of the outcome, here the log of PME, I exponentiate the coefficient of census to obtain exp(-0.071) = 1.073. Subtracting one from this number and multiplying it by 100 results in the percentage change of 7.358% X 1 sd = 4%.

7.9 Full Model

Having tested the independent variables as described in paragraphs 7.1 through 7.8, a full model predicting performance can now be specified. The variables are defined above. The regression model is expressed as in equation 5:

$$log\ PME_{it} = \beta_0 + \sum_{j=1}^{K_{Fund}} \beta_{1j} fund_{jit} + \sum_{j=1}^{K_{Credit\ Market\ Cond.}} \beta_{2j} credit\ market_{jit} + \sum_{j=1}^{K_{Recession}} \beta_{3j} recession_{jit} + \sum_{j=1}^{K_{Previous}} \beta_{4j} log\ PME_{jit-1} \ * \ type_{jit} + \sum_{j=1}^{K_{Type}} \beta_{5j} fund\ type_{jit} + \varepsilon_{it}. \quad (5)$$

Thus, I regress the log of PME for fund *i* in vintage year *t* on a constant and the different categories of variables discussed above: fund specific variables, credit market conditions (including credit spread, credit standards, funding liquidity and aggregate capital flows), recessionary periods and the log of previous fund performance (t-1) as measured by PME, interacted with fund type. Fund type dummy variables are included to hold the average performance effects of each fund type constant. Heteroscedasticity robust standard errors are used throughout all specifications.

Table 10 shows the results. The baseline model is shown in specification 1. As shown in **column 2 of Table 10**, of the fund specific variables "US focus", "industry focus" and "size" only the latter is related to performance, although only marginally significant. Also, extending the baseline model by fund specific variables leaves the explanatory power as measured by the adjusted R^2 almost unchanged.

Next, the impact of credit market conditions, as proxied by the variables described above, are tested. The results are presented in **column 3 of Table 10**:[139] Credit spread, loose credit

[139] It is conceivable that the variables proxying for credit market conditons are multicollinear. However, as measured by the variance inflation factor (VIF) and using pairwise correlation of factors, I find no multicollinearity in specification 3. According to Kutner et al. (2005), the largest VIF value among all independent variables can be used as an indicator of the severity of multicollinearity. A maximum VIF value in excess of 10 is frequently taken as an indication that multicollinearity may be unduly influencing the least squares estimates. The highest VIF value that I find is 1.38. The mean of the VIF values also provides

standards and liquidity as proxied by TED spread are significantly related to performance. A one standard deviation increase in credit spread (= 0.55) increases performance by 4.9%.[140] Loose credit standards as measured by SLOS are negatively related to performance. The PME of funds raised in times of loose credit standards is reduced by an important 7.9%. Also, a worsening of liquidity as measured by (an increase in) the log of TED spread is negatively related to fund performance. A 10% percent increase in spread reduces PD fund performance by an approximate 1.2%. Using the cross-sectional PME of 1.12, for example, a 10% increase in TED spread is associated with a reduction of market outperformance from 12% to 10.7%.[141] Considering the median TED spread of 40.5 basis points and the standard deviation of 26.3 basis points, a one standard deviation increase in TED spread reduces PD fund performance by an approximate 8.5% (26.3 bps over 40.5 bps being equal to approximately 65% or 6.5 X 1.3%). The aggregate amount of capital flowing into the PD industry appears to be unrelated to PD fund performance. Overall, credit risk, credit standards and liquidity appear to explain an important fraction of current fund performance. As measured by the adjusted R^2, the explanatory power increases from an approximate 25% in the baseline model to 37.1% once credit market conditions are considered. Turning to the persistence results of specification three, performance is persistent for direct lending, special situations and venture debt funds, at a level only marginally deviating from model one.

Next, the relation between recessionary periods and performance is studied. The results in **column 4 of Table 10** indicate a strong positive relation between recessionary periods and fund performance. All else equal, a PD fund launched in the recession period of 1990/91 (2001)

information about the severity of potential multicollinearity in terms of how far the estimated standardized regression coefficients are from the true values. Excluding credit spread, for example, results in an average VIF of 1.14. Including credit spread increases VIF minimally to 1.19. Examination of the pairwise correlations does also not indicate any multicollinearity problem.

[140] To interpet the amount of change in the original metric of the outcome, here PME, I exponentiate the coefficient of census in column 3 to obtain exp(0.086) = 1.0906 or -9.07% X 0.55 = 4.9%.

[141] As the ln(1.1) = 0.095, the expected log outperformance is 0.095*-0.12 = -0.0114 in the next period, leading to a PME of exp(-0.0114) = 0.9886. Given the average PME of 1.12 this leads to a PME of 0.9886*1.12 = 1.1072.

performs better by a substantial 36% (31%), the crisis coefficient being significant at the 1%. Contrary to this, the GFC in 2008/9 appears to be unrelated to fund performance. However, as indicated by the adjusted R^2, credit market conditions (as in specification 3) explain more of the variation in PD fund performance than recessions. When replacing credit market conditions by the recession dummies, the adjusted R^2 drops from 37.1% to 27.2%.

Column 5 of Table 10 represents the full specification including fund criteria, credit market conditions and recessionary periods. Again, credit spread and TED spread remain significant, but at a lower level (10% and 5%) and with approximately unchanged coefficients. The amount of capital raised and recessionary periods, however, render insignificant when the full specification in column 5 is used.

Turning to the the post-2007 sub-period[142] in **columns 6 through 8 of Table 10**, the analysis provides some important observations:

First, fund criteria (focus and size) are never significantly related to PD fund performance in all there models. This contrasts the findings for funds operating in the PE industry (Gompers et al., 2009; Ewens & Rhodes-Kropf, 2015) or the analysis of Cumming et al. (2019) related to PD loans.

Second, previous fund performance t-1 appears to be positively related to current fund performance in all models and previous performance is significant for all fund types, with the exception of mezzanine funds, at either the 1% or 5% level. Controlling for credit market conditions or recessionary periods does not change this finding. Based on the results in column 8, a 10% percent increase in lagged performance for direct lending, special situations, distressed debt and venture debt funds increases the average fund specific market outperformance from 10%, 10%, 15% and 6% to an improved outperformance of 14%, 17%, 16% and 9%.

Third, credit market conditions during the vintage year (t) and the following year (t+1) importantly affect subsequent PD fund performance. These credit market conditions include

[142] A comparison to the pre-2007 period is inaccurate given the large number of predictors and the relatively low number of observations for this period.

nonprice aspects proxied by credit standards (SLOS) as well as price aspects as proxied by TED spread. Credit market conditions of the vintage year (t) and the following year (t+1) appear to be a good proxy for a PD fund's returns during its subsequent life. The data suggests that loose credit standards and market liquidity as measured by TED spread are incrementaly important and strong predictors of future PD fund performance. The adjusted R^2 of the regressions increases by 17% from approximately 25% when only prior performance and fund type dummies are used to an approximate 42% when credit market conditions are considered. As taken from column 8,: when credit standards are loose or liquidity lowers (TED spread increases), predicted fund performance is lower. Predicted performance for PD funds that are launched in times of loose credit standards is lower by 9.1%.[143] A 10% increase in TED spread reduces PD fund performance by an approximate 1%. Using the cross-sectional PME of 1.12, for example, a 10% increase in TED spread is associated with a reduction of market outperformance from 12% to 10.9%[144] or an approximate change of 6.5% for a one standard deviation change in TED spread.

Fourth, confirming the PE related studies of Kaplan and Strömberg (2009) and Harris et al. (2014a), I find that fund performance is negatively related to the aggregate amount of capital flowing into the PD asset class (column 7). However, extending the model and allowing for additional variables proxying for credit market conditions, the aggregate amount of capital flowing into the PD asset class (log capital raised) becomes insignificant, suggesting the used credit market conditions are stronger predictors of PD fund performance.

Fifth, turning to the fund type dummy variables and comparing the significance of their coefficients in columns 7 to column 8, it appears that extending the model by credit market conditions picks up the difference in performance of different fund types. This suggests that specific types of PD funds may be correlated with specific credit market conditions.

[143] To interpet the amount of change in the original metric of the outcome, here PME, I exponentiate the coefficient of census in column 8 to obtain exp(0.087) = 1.091 or -9.1%.

[144] As the ln(1.1) = 0.095, the expected log outperformance is 0.095*-0.104 = -0.0099 in the next period, leading to a PME of exp(-0.0114) = 0.9886. Given the average PME of 1.12 this leads to a PME of 0.9886*1.12 = 1.1072.

Finally, Braun et al. (2017) find that persistence in fund performance has substantially declined as the PE sector has matured and become more competitive. Contrasting with their findings for PE funds, I find prevailing PD fund performance persistence, i.e. it does not systematically decline over time, and is driven by the more recent vintages (the post-2007 period) rather than early observations.

8 Robustness

It is conceivable that standard errors of funds managed by the same GP are not independent and identically distributed (i.i.d.). I therefore rerun the regressions clustering standard errors at the GP level and using specification 8 of Table 10 as baseline regression. The result is shown in **Table 11, column 2**. Compared to the baseline regression, the only coefficients of the main analysis that change in significance are the lagged performance of venture debt funds now significant at the 10% instead of the 5% level, and the lagged performance of distressed debt funds, increasing from the 5% to the 1% significance level. However, p-values are almost identical. For the lagged performance of venture debt funds, the p-value increases from $p = 0.049$ to 0.056. For the lagged performance of distressed debt funds, the p-value increases from $p = 2.02$ to 2.68. Overall, clustering standard errors at the GP level to account for the potential correlation of error terms does not affect the presented results in any material way.

Phalippou (2014) shows the sensitivity of fund performance to the choice of the benchmark. While it has been demonstrated that PD funds outperform the market using both the investment grade - and the high yield -benchmark, it is conceivable that the analyses in Section 7 are affected by the use of the high yield instead of the investment grade benchmark. I therefore re-run specification 8 of Table 8 using the log of PME_{HY} instead of the log of PME_{IG} as dependent and lagged variable. The result is shown in **Table 11, column 3**. As in the baseline, a state of loose credit standards and TED spread seem to drive PD fund performance. The significance of these coefficients now increase to the 1% level. Additionally, industry focus becomes significant at the 10% level. Persistence of venture debt funds drops and becomes insignificant, while it remains detected for those fund types identified in the baseline regression. However, adjusted R2 drops to a level of 27.6%. It appears that the results are sensitive to the choice of the benchmark. This, however, does not to invalidate the findings of this study in a material way.

Persistence results can be biased because of time period overlap or investment overlap. If so, persistence should decline with the amount of time that elapses between the vintage years of PD funds. To test for the possibility of a bias induced by time period or investment overlaps, I interact the log of previous PME with the log of time (years) between the current and the previous fund PME. This is methodologically in line with Kaplan and Schoar (2005), who likewise control for the potential effects from time period overlaps. As is shown in **Table 11, column 4**, the coefficient on the interaction term is negative but statistically not significant. This result suggests that my persistence results are not caused by an effect of time overlap. This robustness test fails however, to distinguish between time period and investment overlaps. One way to accomplish this distinction would be to include previous funds with vintage years at least 5 years distant from current fund vintages. This would likely make an investment overlap very little. Doing this reduces the sample size to only 38 observations, however. It can therefore not be excluded that current and previous funds of a particular GP have some investments in common and that this could mechanically induce persistence.

Other than in this study, Kaplan and Schoar (2005) and Braun et al. (2017) include funds that are largely liquidated in their studies. Braun et al. (2017), for example, use funds in which at least 50% of the capital invested has been realized. Although in line with Harris et al. (2014b) and other researchers, who use funds with high unrealized assets, I control for a potential upward bias in reported performance originating from manipulations of self-reported NAVs. Investigating the variation in returns as measured by PME_{IG} I test the difference in performance means for analysed funds with low self-reported NAVs (below 50%) versus those with high (beyond 50%) self-reported NAVs. Using a student t-test and the Wilcoxon ranksum test for the equality of performance between funds with a remaining value to paid in capital of below 50% and those above this level. I find no statistically significant difference in performance across the two groups for either the overall sample period (t=0.8, z=1.5) or the post-2007 sub-period (t=1.4, z=1.2). This finding is in line with the relatively low changes in performance when adjusting self-reported NAVs in **Tables 2 and 3**. To analyse this further, I control whether the regression results are sensitive to the level of self-reported NAVs. In **Table 12**, I let the level of self-reported NAVs (remaining value to paid-in capital, "rvpi") increase in increments of 25% from <50% to <150% in columns 1 through 5. Column 6 is the baseline regression including all observattions. Specification 8 is now the baseline, as it includes all the observations.The results do not change importantly when rvpi increases from a very low level in column 1 to the maximum level in column 6. Also, the adjusted R^2 grows only little from 30.7% to 36.3%. The data suggests that using only largely liquidated funds for reasons of potential NAV manipulation is not a necessary condition for accurate performance evaluations when researching PD funds.

Next, to control for a potential upward bias in performance resulting from GPs of funds with bad performance that do not disclose cash flow data, I compare the larger Preqin sample to the sample of this study. The larger sample consists of 921 funds of which 729 report the internal rate of return (IRR). I conduct two analyses to detect a potential bias. First, I take the IRR information as available from Preqin and for the same funds researched in this study and compare the reported IRRs to those calculated from timed cash flows. I call this the matched sample. Second, I exclude from the larger sample those funds studied in this paper. This results in two mutually exclusive samples that I call the unmatched samples. The cross-sectional IRR of the matched sample shows only marginal differences in IRRs. Overall, the IRR of the matched sample amounts to an average 10.36%, whereas I find 10.61%. Sorted by fund type, the IRR differences are small and amount to 0.01%, -0.09%, -1.01%, -0.18% and -0.40% for mezzanine, direct lending, special situations, distressed debt and venture debt funds. Likewise, the differences as sorted by IRR quartiles are minimal. This suggests that IRRs of funds that disclose cash flows to Preqin are approximately correct. The analysis of the unmatched samples reveals a different result: I find that the average performance of this mutually exclusive group of funds deviates importantly from the average values computed in this study. Overall, the IRR of the unmatched sample amounts to an average IRR of 12.7%, whereas I find 10.6%. Sorted by fund type, the IRR differences are much larger and amount to 1.7%, -0.4%, 4.3%, 4.6% and 14.8% for mezzanine, direct lending, special situations, distressed debt and venture debt funds. This does not necessarily imply that the IRRs of the unmatched sample are manipulated or exaggerated. However, they still deviate substantially from the IRRs found in this study, suggesting there may exist an upward bias in performance of funds that do not provide cash flow data. Potential reasons for such an upward bias have been discussed earlier. Also, it can be taken from this observation that the performance data reported in this study can be considered conservative or biased downwards rather than upwards.

9 Conclusions

Over their lifetime, PD funds outperform public bond markets, as measured by the Bloomberg Barclays US Corporate Bond Index and using the Kaplan and Schoar (2005) PME, by 12% in the cross-section and by an average 16% if sorted by vintage years. I find a large performance difference between top- and bottom quartile funds. While the best funds outperform the market by 44%, the worst underperform it by 16%. Annualizing market outperformance reveals attractive alpha of approximately 2% in the cross-section and 6% for top- and -2.6% for bottom-quartile funds. This alpha is confirmed by the application of a generalized method of moments approach. The observed interquartile range of 60% in terms of aggregate lifetime outperformance and 8.6% in terms of annualized alpha makes fund selection a first-order concern.

I relax the assumption that beta equals one as in Kaplan and Schoar (2005) and use the method to estimate risk and return of nontraded assets from cash flows as proposed by Driessen et al. (2012). The data suggests that betas of PD funds are reliably different from one. This finding is in line with Munday et al. (2018), who find relatively low betas and high alphas for PD funds.

Persistence in returns across subsequent funds of a partnership may help to select good and avoid bad performing funds. Prima facie, it appears to be a good strategy to invest in PD funds managed by GPs that have previously managed top-quartile funds. Relative to a randomized strategy and based on quartile transition probabilities, the average increase in in market outperformance to be achieved from such prediction would have been 8% for the overall sample period or 13% for the post-2007 sub-period. However, credit market conditions affect PD fund performance importantly and should be considered when selecting PD funds: performance is significantly and negatively related to credit market conditions such as loose credit standards and funding liquidity as measured by TED spread.

Given that the betas in my study are statistically not distinguishable from zero and the assumption underlying the Driessen et al.'s (2012) method that alphas and betas are the same across a cross-section of funds, I conclude with the suggestion that future research might shed more light on this important topic. Specifically, the risk and return of specific investment strategies of PD funds (mezzanine, direct lending etc.) could be analysed in respect to their alphas and betas.

10 Tables

Table 1: Descriptive Statistics

This table reports descriptive statistics of PD funds with vintage years 1986 through 2016 by fund type. Size is measured as the dollar amount that is committed to a fund in 2001 dollars. Standard deviation is given in parentheses for size and maturity. Maturity (L) is the maturity for liquidated funds, that is funds with undistributed assets below 5% of total paid-in capital. Maturity (LL) is the maturity for largely liquidated funds, that is funds with undistributed assets below 50% of total paid-in capital. Geographical focus indicates the main focus of funds in % and per geographical region (US, Europe, Asia, other regions). Industry focus indicates in % whether a fund is focused on one industry or a group of industries that logically belong together as opposed to being diversified (various industries wiht no logical link).

Sample	All funds	Mezzanine	Direct Lending	Special Situations	Distressed Debt	Venture Debt
No. of observartions	347	117	54	32	127	17
Relative weight in %	100.0	33.7	15.6	9.2	36.6	4.9
Size (mn USD), mean	950.4	643.9	649.5	796.5	1497.9	215.7
std(x)	(1150.2)	(961.6)	(666.4)	(833.6)	(1382.5)	(205.4)
Maturity (L), mean	12.6	14.0	9.7	11.6	11.7	11.0
std(x)	(3.3)	(2.9)	(2.1)	(3.5)	(3.2)	(3.5)
Maturity (LL), mean	10.6	12.4	6.3	9.5	10.2	10.8
std(x)	(3.8)	(3.7)	(3.0)	(3.1)	(3.4)	(3.3)
Geographical focus (%)						
United States	83.9	88.9	72.2	65.6	86.6	100.0
Europe	12.7	9.4	25.9	18.8	10.2	0.0
Asia	2.9	0.0	1.9	15.6	3.1	0.0
Other regions	0.6	1.7	0.0	0.0	0.0	0.0
Industry focus (%)						
Focused	44.1	63.3	35.2	37.5	25.2	94.1
Diversified	55.9	36.7	64.8	62.5	74.8	5.9

Table 2: Internal Rate of Return (IRR) & Investment Multiple (TVPI) of Private Debt (PD) Funds

This table reports fund level characteristics of the sample of 347 PD funds by fund vintage years. It shows the number of funds per vintage year and the mean fund size in millions of USD, that is the amount of capital committed to a fund in 2001 dollars. Fund maturity is from the first to the last cash flow observed. The unrealized remaining value (NAV) of a fund is scaled by the total paid-in contribution of a Limited Partner (LP) to a fund and expressed in % (**RVPI**). All performance measures are net of fees and calculated myself, not Preqin, from the cash flows from and to LPs. **IRR_{CF}** is the unadjusted IRR as calculated from the cash flows and treating self-reported NAVs as market values distributed to LPs if a fund is not liquidated. **$IRR_{adjusted}$** is based on self-reported NAVs of non-liquidated funds being written down by 5% if the fund's age in days is below the mean age of all liquidated PD funds and written down by 30% if a fund's age is above or equal to the mean fund age of liquidated funds. The same NAV write-offs apply to the total value to paid-in relation (TVPI) and the Public Market Equivalent (PME). The **$TVPI_{CF}$** is the sum of all distributions to LPS plus the remaining value, scaled by all contributions from an LP. Top, 2nd, 3rd and bottom quartile performance is given for all performance measures. Also, descriptives and performances are given per fund type (mezzanine, direct lending, distressed debt, special situations debt and venture debt).

(1)	(2)	(3)	(4)	(5)	(6)				(7)			
					Internal Rate of Return (IRR)				Total Value to Paid In Relation (TVPI)			
	Nbr. of funds	Fund maturity	Fund size (mean, mn of USD)	RVPI (NAV in % to paid-in)	IRR_{CF}		$IRR_{adjusted}$		$TVPI_{CF}$		$TVPI_{adjusted}$	
					Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel A: Cross-Section												
All	347	12.84 [1]	950.4	45.58	0.11	9.47	0.09	8.70	1.36	1.28	1.33	1.25
Top	86	8.31	928.6	43.93	0.23	0.19	0.22	0.17	1.84	1.73	1.83	1.70
2nd qrt	87	6.79	1154.0	52.80	0.12	0.11	0.11	0.10	1.38	1.37	1.36	1.34
3rd qrt	87	6.52	826.0	58.30	0.08	0.08	0.07	0.07	1.21	1.21	1.18	1.18
Bottom	87	8.98	947.7	27.75	0.00	0.02	-0.01	0.01	1.00	1.06	0.98	1.02
Mezz.	117	9.34	643.9	37.66	0.09	0.10	0.08	0.09	1.37	1.31	1.35	1.29
Direct	54	3.98	649.5	69.62	0.10	0.09	0.07	0.08	1.21	1.18	1.17	1.14
Spec. Sit.	32	6.12	796.5	64.77	0.12	0.10	0.11	0.09	1.43	1.34	1.41	1.32
Distr.	127	8.04	1497.9	39.02	0.11	0.08	0.10	0.06	1.30	1.22	1.27	1.18
Venture	17	8.17	215.7	36.74	0.08	0.09	0.07	0.07	1.31	1.24	1.29	1.23
Panel B: By Vintage Year												
1986	2	15.38	160.00	0.00	0.02	0.02	0.02	0.02	1.32	1.32	1.32	1.32
1987	1	13.89	327.22	0.00	0.18	0.18	0.18	0.18	2.62	2.62	2.62	2.62
1988	1	13.26	102.40	0.00	0.13	0.13	0.13	0.13	2.12	2.12	2.12	2.12
1990	2	14.51	346.78	0.00	0.24	0.24	0.24	0.24	2.17	2.17	2.17	2.17
1991	2	13.17	214.94	0.00	0.16	0.16	0.16	0.16	1.70	1.70	1.70	1.70
1992	4	11.80	106.48	0.00	0.07	0.08	0.07	0.08	1.15	1.23	1.15	1.23
1993	1	13.88	118.22	0.00	0.32	0.32	0.32	0.32	3.40	3.40	3.40	3.40
1994	3	14.47	173.01	0.00	0.03	-0.03	0.03	-0.03	1.15	0.89	1.15	0.89
1995	2	16.89	291.50	0.00	0.05	0.05	0.05	0.05	1.22	1.22	1.22	1.22
1996	4	13.94	464.66	0.00	0.02	0.06	0.02	0.06	1.20	1.34	1.20	1.34
1997	5	15.77	813.96	0.00	0.14	0.12	0.14	0.12	1.90	1.67	1.90	1.67
1998	5	14.09	406.05	3.15	0.08	0.07	0.08	0.06	1.35	1.34	1.35	1.34
1999	8	15.36	615.67	0.30	0.10	0.12	0.10	0.12	1.44	1.44	1.44	1.44
2000	8	13.63	726.45	1.06	0.14	0.12	0.14	0.12	1.48	1.48	1.48	1.46
2001	10	13.62	975.21	0.34	0.20	0.19	0.20	0.19	1.76	1.59	1.76	1.59
2002	7	12.76	509.88	2.20	0.23	0.11	0.23	0.11	1.53	1.38	1.52	1.38
2003	7	12.43	1051.92	1.04	0.08	0.10	0.08	0.10	1.39	1.47	1.39	1.47
2004	5	12.33	670.40	16.01	0.08	0.09	0.08	0.09	1.45	1.54	1.43	1.49
2005	16	12.15	574.85	10.61	0.06	0.07	0.06	0.06	1.37	1.32	1.35	1.32
2006	18	11.11	1592.82	14.83	0.08	0.08	0.08	0.08	1.44	1.32	1.44	1.32
2007	16	10.09	1963.20	13.64	0.09	0.07	0.09	0.07	1.36	1.36	1.35	1.36
2008	21	8.80	1400.87	18.61	0.11	0.12	0.11	0.11	1.48	1.45	1.48	1.44
2009	13	7.58	812.68	41.50	0.15	0.15	0.14	0.15	1.54	1.61	1.52	1.61
2010	19	7.37	776.58	30.86	0.09	0.10	0.08	0.10	1.37	1.38	1.36	1.35
2011	19	6.36	1103.65	53.88	0.10	0.10	0.10	0.09	1.40	1.33	1.37	1.29
2012	27	5.10	1163.81	69.86	0.11	0.08	0.09	0.08	1.30	1.23	1.27	1.19
2013	33	4.28	859.07	78.78	0.09	0.08	0.07	0.07	1.23	1.21	1.19	1.18
2014	31	3.20	858.08	86.84	0.13	0.11	0.11	0.09	1.24	1.21	1.20	1.16
2015	40	2.42	937.54	93.07	0.10	0.10	0.06	0.08	1.14	1.15	1.09	1.10
2016	17	1.62	864.03	93.40	0.10	0.09	0.04	0.04	1.08	1.08	1.04	1.04
Total	**347**	**7.68**	**950.4**	**45.58**	**0.11**	**0.09**	**0.09**	**0.09**	**1.36**	**1.28**	**1.33**	**1.25**

1 Fund maturity indicated for largely liquidated funds, i.e. RVPI < 50%

Table 3: Public Market Equivalent (PME) of Private Debt (PD) Funds

This table reports fund level characteristics of the sample of 347 PD funds by fund vintage years. It shows the number of funds per vintage year and relative fund performance as measured by the Kaplan and Schoar (2005) PME. All performance measures are net of fees and calculated myself, not Preqin, from the cash flows from and to LPs. The Public Market Equivalent (**PME**) compares the investment in a PD fund to an investment in the benchmark. The Bloomberg Barclays US Corporate Bond Total Return Index Baa [Bloomberg Ticker: LCB1TRUU] is used to calculate the PME in column 3, representing investment grade (IG) bonds. The Bloomberg Barclays US Corporate High Yield Index is used to calculate the PME given in column 4 [Bloomberg Ticker: LF98TRUU]. Securities are classified as high yield if the middle rating of Moody's, Fitch and S&P is Ba1/BB+/BB+ or below. All cash contributions from and distributions to LPs are discounted using the total return of this index (PME_{CF}). Self-reported NAVs are treated as market values distributed to LPs if a fund is not liquidated. The present value (PV) of all distributions are scaled by the PV of all contributions to calculate the PME. A PD fund with a PME greater than 1 outperformed the index net of all fees. Adjusted PMEs ($\mathbf{PME_{adjusted}}$) represent calculations based on adjusted self-reported NAVs of non-liquidated funds. These NAVs are written down by 5% if the fund's age in days is below the mean age of all liquidated PD funds and written down by 30% if a fund's age is above or equal to the mean age. Top, 2nd, 3rd and bottom quartile performance is given for all performance measures. Also, descriptives and performances are given per fund type (mezzanine, direct lending, distressed debt, special situations debt and venture debt). Annualized alpha (α) and its standard deviation (σ) is depicted in column 5 as calculated from the investment grade benchmark and in column 6 as calculated from the high yield benchmark. For each fund, the annualized α is calculated by $(PME_i)^\wedge(1/y_i) - 1$, whereas y_i equals to the fund duration as calculated from the first to the last cash flow in years.

Panel A: Cross Section

(1)	(2)	(3)				(4)				(5)		(6)	
		Public Market Equivalent (PME) Bloomberg Barclays US Corp. TRI IG				Public Market Equivalent (PME) Bloomberg Barclays US Corp. TRI HY				Annualized Alpha		Annualized Alpha	
Fund vintage	Obs.	PME_{CF}		$PME_{adjusted}$		PME_{CF}		$PME_{adjusted}$		PME_{IG}		PME_{HY}	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	α	σ	α	σ
All	347	1.12	1.10	1.09	1.07	1.07	1.05	1.05	1.02	1.99	4.44	1.02	4.18
Top	86	1.44	1.34	1.42	1.33	1.37	1.27	1.35	1.26	5.96	4.80	4.88	4.63
2nd qrt	87	1.15	1.14	1.12	1.12	1.09	1.09	1.07	1.07	3.15	2.42	2.17	1.66
3rd qrt	87	1.06	1.06	1.03	1.04	1.01	1.01	0.98	0.99	1.46	1.25	0.29	0.99
Bottom	87	0.84	0.89	0.83	0.87	0.80	0.84	0.78	0.83	-2.57	3.18	-3.23	3.19
Mezz.	117	1.11	1.09	1.09	1.08	1.06	1.06	1.05	1.03	1.12	4.21	0.51	4.22
Direct	54	1.10	1.09	1.07	1.06	1.05	1.04	1.01	1.01	3.08	3.42	1.32	2.69
Spec. Sit.	32	1.10	1.08	1.07	1.04	1.05	1.02	1.02	1.00	2.54	7.54	1.84	7.72
Distr.	127	1.15	1.13	1.13	1.10	1.09	1.08	1.07	1.05	2.25	4.04	1.25	3.55
Venture	17	1.06	1.03	1.04	1.00	1.01	0.99	0.99	0.96	1.17	2.35	0.27	2.18
Panel B: By Vintage Year													
1986	2	.	.	.	.	0.71	0.71	0.71	0.71	.	.	-2.53	2.68
1987	1	.	.	.	.	1.48	1.48	1.48	1.48	.	.	2.87	.
1988	1	1.19	1.19	1.19	1.19	1.09	1.09	1.09	1.09	1.34	.	0.68	.
1990	2	1.50	1.50	1.50	1.50	1.27	1.27	1.28	1.28	5.76	7.68	3.77	5.42
1991	2	1.29	1.29	1.29	1.29	1.18	1.18	1.18	1.18	2.00	2.30	1.30	2.12
1992	4	0.89	1.01	0.89	1.01	0.86	0.98	0.86	0.98	-1.06	3.00	-1.37	2.94
1993	1	2.42	2.42	2.42	2.42	2.37	2.37	2.37	2.37	6.56	.	6.42	.
1994	3	0.86	0.71	0.86	0.71	0.87	0.75	0.87	0.75	-1.20	2.31	-1.07	1.93
1995	2	0.88	0.88	0.88	0.88	0.89	0.89	0.89	0.89	-0.85	2.15	-0.78	2.24
1996	4	0.86	0.95	0.86	0.95	0.93	1.03	0.93	1.03	-1.51	3.38	-1.04	3.47
1997	5	1.38	1.25	1.38	1.25	1.50	1.31	1.50	1.31	1.42	3.41	1.88	3.56
1998	5	1.03	1.03	1.03	1.01	1.11	1.19	1.11	1.94	0.22	1.03	0.76	1.16
1999	8	1.15	1.12	1.15	1.12	1.13	1.18	1.13	1.18	0.74	1.62	0.76	1.27
2000	8	1.17	1.17	1.72	1.17	1.12	1.13	1.12	1.13	1.14	1.28	0.73	1.45
2001	10	1.41	1.31	1.41	1.31	1.26	1.20	1.26	1.20	2.41	1.19	1.56	1.04
2002	7	1.27	1.15	1.27	1.15	1.16	1.06	1.16	1.06	1.94	3.17	1.03	2.96
2003	7	1.12	1.18	1.12	1.18	1.04	1.08	1.04	1.08	0.81	2.39	0.22	2.16
2004	5	1.11	1.13	1.10	1.13	1.02	1.07	1.00	1.07	0.15	2.60	-0.79	3.52
2005	16	0.96	0.98	0.96	0.97	0.91	0.91	0.91	0.90	-0.43	1.50	-0.85	1.54
2006	18	1.02	1.00	1.01	1.00	0.95	0.96	0.95	0.95	-0.34	3.14	-0.91	3.17
2007	16	0.98	0.97	0.97	0.97	0.90	0.91	0.90	0.91	-0.34	2.36	-1.15	2.21
2008	21	1.07	1.09	1.06	1.07	0.95	0.93	0.95	0.93	0.54	2.05	-0.84	2.21
2009	13	1.25	1.20	1.24	1.19	1.16	1.05	1.15	1.05	3.19	3.57	2.08	3.44
2010	19	1.15	1.17	1.14	1.16	1.09	1.11	1.08	1.09	1.65	3.00	0.92	2.86
2011	19	1.20	1.16	1.18	1.12	1.14	1.10	1.12	1.08	2.41	4.37	1.75	3.76
2012	27	1.16	1.09	1.13	1.06	1.14	1.06	1.11	1.04	3.01	5.70	2.57	5.59
2013	33	1.08	1.09	1.07	1.06	1.08	1.06	1.05	1.02	2.06	3.45	1.74	3.29
2014	31	1.16	1.13	1.11	1.09	1.10	1.07	1.07	1.03	5.07	6.42	3.50	6.41
2015	40	1.07	1.09	1.03	1.05	1.02	1.04	0.98	1.00	2.81	6.10	0.64	5.89
2016	17	1.07	1.08	1.03	1.03	1.04	1.02	0.99	0.98	4.73	5.18	2.01	4.12
Total	**347**	**1.17**	**1.16**	**1.18**	**1.14**	**1.12**	**1.11**	**1.11**	**1.13**	**1.58**	**3.24**	**0.86**	**3.05**

Table 4:
Risk and Abnormal Performance of Private Debt Funds

This table reports alphas and betas of the sample of 28 value weighted portfolios PD funds, sorted by vintage year, relative to different benchmarks and calculated from quarterly cash flows. The method to estimate alpha and beta of nontraded assets from cash flows of Driessen et al. (2012) is used. All cash flows are net of fees. A 1-factor market model is used. Panel A presents the results based on the he Bloomberg Barclays US Corporate Bond Total Return Index Baa [Bloomberg Ticker: LCB1TRUU] as a benchmark. Panel B gives the results using the Bloomberg Barclays US Corporate High Yield Index [Bloomberg Ticker: LF98TRUU] as benchmark. Panel C compares PD fund cash flows to US stocks, the data are from the Center for Research in Security Prices (CRSP) provided by Kenneth R. French's homepage (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Standard errors are in parenthesis, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: IG-Benchmark	
	α	β
Alpha and beta	2.46***	-0.13
std.err.	(0.42)	(0.35)
No. of obs. (portfolios)	28	
	Panel B: HY-Benchmark	
	α	β
Alpha and beta	2.19***	0.05
std.err.	(0.50)	(0.30)
No. of obs. (portfolios)	28	
	Panel C: US Stocks Benchmark	
	α	β
Alpha and beta	1.62***	0.43**
std.err.	(0.39)	(0.20)
No. of obs. (portfolios)	28	

Table 5:
Performance of first-time and one-time PD funds

This table reports performance metrics for the cross-section as a baeline (column A), for one-time funds (column B), that is funds that enter the sample but no subsequent fund managed by the same GP is observed in the dataset, and for first-time funds (column C), that is funds that enter the sample for the first time and for wich at least one follow-on fund managed by the same GP is observed. Column D shows the performance metrics if one-time funds are excluded from the sample. Column E shows the difference from columns D and A and indicates the potential effects from attrition. Standard deviation and number of observations in parenthesis. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, comparing the performance metrics of one-time and first-time funds to those funds in the cross-section that are no one-time or first-time funds.

Metric	(A) Cross-section	(B) One-time funds	(C) First-time funds	(D) Cross-section w/o one-time	(E) Difference D - A
IRR	10.61	6.7***	12.98***	11.69	1.08
	(10.15; 347)	(10.53; 75)	(8.40; 78)	(9.79; 272)	
TVPI	1.36	1.18***	1.52***	1.41	0.05
	(0.37; 347)	(0.30; 75)	(0.44; 78)	(0.38; 272)	
PME_{IG}	1.12	1.01***	1.20***	1.15	0.03
	(0.27; 341)	(0.26; 74)	(0.31; 75)	(0.26; 267)	
PME_{HY}	1.07	0.96***	1.15***	1.10	0.03
	(0.26; 347)	(0.24; 75)	(0.30; 78)	(0.26; 272)	
α_{IG}	1.99	0.87***	2.25	2.30	0.31
	(4.44; 341)	(5.69; 74)	(3.24; 75)	(3.98; 267)	
α_{HY}	1.02	-0.32***	1.52	1.39	0.37
	(4.18; 347)	(5.90; 75)	(2.83; 78)	(3.82; 272)	

Table 6: Fund Persistence Regressions

This table shows OLS regresssions of current fund performance (PME_{it}) on previous fund performance (PME_{it-1}) in Panels A. In Panel B, positive lagged performance $PME_{it-1(+)}$ and negative lagged performance $PME_{it-1(-)}$ and the investment grade benchmark are used. PME is expressed in natural logarithms (log). The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}, the investment grade (IG) benchmark in columns one through three. The Bloomberg Barclays US Corporate High Yield Index is used to calculate PME_{HY}, the high yield (HY) benchmark, in columns four through six. The regressions incluce fund type fixed effects and vintage year fixed effects. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: PME persistence using the investment grade (IG) and high yield (HY) benchmark

VARIABLES	(1) All periods PME_{IG}	(2) Pre-2007 periods PME_{IG}	(3) Post-2007 period PME_{IG}	(4) All periods PME_{HY}	(5) Pre-2007 period PME_{HY}	(6) Post-2007 period PME_{HY}
log of PME_{t-1}	0.171**	0.0930	0.234***	0.169**	0.0913	0.243***
	(0.0788)	(0.255)	(0.0691)	(0.0845)	(0.291)	(0.0722)
mezzanine	0.0767**	0.0669	0.0477	0.0534*	0.00822	0.0305
	(0.0330)	(0.112)	(0.0297)	(0.0299)	(0.107)	(0.0274)
direct lending	0.0174	-0.0438	0.0178	-0.00292	-0.0892	-0.00175
	(0.0248)	(0.160)	(0.0234)	(0.0242)	(0.173)	(0.0237)
special situations	-0.00293		-0.0131	-0.0102		-0.0223
	(0.112)		(0.108)	(0.111)		(0.105)
distressed debt	0.0209	-0.0693	0.0361	-0.00776	-0.117	0.00782
	(0.0316)	(0.0874)	(0.0305)	(0.0306)	(0.0912)	(0.0297)
venture debt	0.00417	-0.102	0.0141	-0.0332	-0.144	-0.0351
	(0.0447)	(0.148)	(0.0464)	(0.0447)	(0.158)	(0.0467)
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	184	49	135	187	51	136
Adjusted R^2	0.386	0.260	0.389	0.294	0.162	0.266

Panel B: PME persistence using positive (+) and negative (-) PME_{t-1}, IG benchmark

VARIABLES	(1) All periods, positive $PME_{t-1(+)}$	(2) All periods, negative $PME_{t-1(-)}$	(3) Pre-2007 period, positive $PME_{t-1(+)}$	(4) Pre-2007 period negative $PME_{t-1(+)}$	(5) Post-2007 period positive $PME_{t-1(+)}$	(6) Post-2007 period, negative $PME_{t-1(-)}$
log of PME_{t-1}	0.116	0.0348	-0.0452	n.a.	0.302**	0.0401
	(0.132)	(0.234)	(0.253)		(0.140)	(0.227)
mezzanine	0.0692*	0.0163	0.0992		0.0171	0.00553
	(0.0370)	(0.110)	(0.107)		(0.0341)	(0.119)
direct lending	0.0221	0.0888**			0.00700	0.0896**
	(0.0290)	(0.0344)			(0.0266)	(0.0334)
special situations	0.0850	-0.187			0.0304	-0.200
	(0.137)	(0.157)			(0.134)	(0.169)
distressed debt	-0.00327	0.108	-0.0440		-0.00421	0.0982
	(0.0366)	(0.0967)	(0.0859)		(0.0361)	(0.103)
venture debt	-0.00861	0.0924			-0.0255	0.0717
	(0.0564)	(0.0791)			(0.0456)	(0.125)
Year fixed effects	Y	Y	Y		Y	Y
Observations	144	40	43		101	34
Adjusted R^2	0.427	0.405	0.350		0.455	0.357

Table 7: Quartile Transition Probabilities of PD Funds based on PME

All funds for which a follow-on fund is available are sorted into performance quartiles. I calculate the conditional probability that a partnership's next fund will either stay in the same performance quartile or into one of the other three quartiles The results in Panel A are for he wohole sample period, Panels B and C for the pre-2007 and post-2007 sub-periods. For example, as in Panel A, funds with a prior fund in the top quartile remain in the top quartile of successive funds with a probability of 39.1%. A flip of a bottom quartile fund into the top quartile is expected to happen in 13.% of cases. A flip from the top quartile to the bottom quartile can be expected in 15.25 of cases . The expected return given previous quartile performance and the probability distribution of funds staying in the same or switching into another quartile is calculated in Panel D. Selecting PD funds with previous top-quartile performance in Panel A, for example, yields an expected PME of 1.2.

Panel A: Quartile Transition Probabilities, whole sample / **Panel D**

	Top-Quartile	2nd	3rd	Bottom-Quartile	%/[n]	*E* (PME) | PQ
Previous Quartile	%	%	%	%		
Top-Quartile	39.13	23.91	21.74	15.22	100.00	1.20
[n]	[18]	[11]	[10]	[7]	[46]	
2nd Quartile	19.15	31.91	34.04	14.89	100.00	1.13
[n]	[9]	[15]	[16]	[7]	[47]	
3rd Quartile	27.66	29.79	21.28	21.28	100.00	1.15
[n]	[13]	[14]	[10]	[10]	[47]	
Bottom-Quartile	13.04	23.91	26.09	36.96	100.00	1.05
[n]	[6]	[11]	[12]	[17]	[46]	

Panel B: Quartile Transition Probabilities, pre-2007 period

	Top-Quartile	2nd	3rd	Bottom-Quartile	%/[n]	*E* (PME) | PQ
Previous Quartile	%	%	%	%		
Top-Quartile	30.00	35.00	15.00	20.00	100.00	1.16
[n]	[6]	[7]	[3]	[4]	[20]	
2nd Quartile	25.00	12.50	50.00	12.50	100.00	1.14
[n]	[2]	[1]	[4]	[1]	[8]	
3rd Quartile	46.15	23.08	23.08	7.69	100.00	1.24
[n]	[6]	[3]	[13]	[1]	[13]	
Bottom-Quartile	0.00	30.00	30.00	40.00	100.00	1.00
[n]	[0]	[3]	[3]	[4]	[10]	

Panel C: Quartile Transition Probabilities, post-2007 period

	Top-Quartile	2nd	3rd	Bottom-Quartile	%/[n]	*E* (PME) | PQ
Previous Quartile	%	%	%	%		
Top-Quartile	50.00	19.23	23.08	7.69	100.00	1.25
[n]	[13]	[5]	[6]	[2]	[26]	
2nd Quartile	20.51	30.77	33.33	15.38	100.00	1.13
[n]	[8]	[12]	[13]	[6]	[39]	
3rd Quartile	20.59	29.41	17.65	32.35	100.00	1.09
[n]	[7]	[10]	[6]	[11]	[34]	
Bottom-Quartile	16.67	25.00	16.67	41.67	100.00	1.05
[n]	[6]	[9]	[6]	[15]	[36]	

Table 8: Fund Persistence Regressions by Fund Type

This table shows OLS regresssions of current fund performance (PME_{it}) on previous fund performance (PME_{it-1}), interacted with fund types mezzanine, direct lending, special situations, distressed and venture debt funds and including dummy variables for fund types. PME is expressed in natural logarithms. The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}, the investment grade (IG) benchmark. The Bloomberg Barclays US Corporate High Yield Index is used to calculate PME_{HY}, the high yield (HY) benchmark. All regressions incluce vintage year fixed. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

VARIABLES	(1) All periods PME_{IG}	(2) Pre-2007 period PME_{IG}	(3) Post-2007 period PME_{IG}	(4) All periods PME_{HY}	(5) Pre-2007 period PME_{HY}	(6) Post-2007 period PME_{HY}
mezzanine X PME_{t-1}	0.115	0.350	-0.0501	0.120	0.346	-0.0505
	(0.176)	(0.515)	(0.120)	(0.157)	(0.493)	(0.0862)
direct lending X PME_{t-1}	0.395***		0.423***	0.310**		0.373***
	(0.0998)		(0.0985)	(0.135)		(0.132)
special situations X PME_{t-1}	0.672**		0.679***	0.576**		0.595***
	(0.265)		(0.259)	(0.232)		(0.227)
distressed debt X PME_{t-1}	0.0573	-0.0575	0.160**	0.0943	-0.0518	0.228**
	(0.109)	(0.338)	(0.0788)	(0.115)	(0.379)	(0.0877)
venture debt X PME_{t-1}	0.358*	1.956	0.262	0.167	-0.824	0.232
	(0.185)	(1.479)	(0.208)	(0.245)	(2.063)	(0.309)
mezzanine	0.0829**	0.00903	0.0902**	0.0574*	-0.0363	0.0558*
	(0.0409)	(0.144)	(0.0367)	(0.0324)	(0.138)	(0.0283)
direct lending	-0.00249	-0.0449	-0.000839	-0.00913	-0.115	-0.00758
	(0.0312)	(0.166)	(0.0313)	(0.0277)	(0.162)	(0.0289)
special situations	-0.130		-0.127	-0.0978		-0.0988
	(0.124)		(0.121)	(0.113)		(0.111)
distressed debt	0.0359	-0.0393	0.0462	-0.000800	-0.0848	0.0137
	(0.0324)	(0.0989)	(0.0317)	(0.0312)	(0.103)	(0.0304)
venture debt	-0.00832	0.0752	0.0136	-0.0347	-0.270	-0.0304
	(0.0469)	(0.199)	(0.0567)	(0.0467)	(0.301)	(0.0618)
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	184	49	135	187	51	136
Adjusted R^2	0.403	0.234	0.422	0.299	0.128	0.289

Table 9:
Factors Affecting Performance and Persistene
(Simple OLS Regressions)

This table shows OLS regresssions of current fund performance (PME_E) on previous fund performance (PME_{E-1}), interacted with fund types mezzanine, direct lending, special situations, distressed and venture debt funds. PME is expressed in natural logarithms. The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}. It is used as the investment grade (IG) benchmark. Column 1 controls for US focus, a dummy variable indicating whether a PD fund focuses geographically on the US. Column 2 controls for industry focus a dummy variable indicating whether a fund invests in one or related industries as opposed to following a diversified, industry agnostic strategy. Column 3 includes fund size. Aggregatre capital raised (column 4) is the aggregate amount of capital raised in the vintage year (t) plus the following year (t+1) as reported by Preqin. SLOS (column 5) is the average changes in the credit standars as reported in the Federal Reserve's Senior Loan Officer Survey (SLOS) of periods t and (t+1). It is indicated as a positive (negative) percentage change of loan officers tightening (loosening) their credit standards and described in Franzoni et al. (2012). Column 6 shows the effects of the average level of TED spread of periods t and (t+1), which is the difference between interest rate on short-term (3 months) US government debt and the interest rate on interbank loans. NBER recessions (column 7) is a dummy variable taking the value of one if a fund was launched (vintage year) in a recession period as indicated by the National Bureau of Economic Research (NBER). Credit spread (colulmn 8) is calculated as the average spread of periods t and (t+1) between Moody's Seasoned Baa Corporate Bond and the 10-Year Treasury Constant Maturity, data are from the Federal Reserve St. Louis. Fund type fixed effects are used. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

VARIABLES	(1) usfocus	(2) industry focus	(3) fund size	(4) capital raised	(5) credit standards	(6) TED spread	(7) NBER recession	(8) credit spread
US focus	-0.00680							
	(0.0381)							
industry focus		0.0482						
		(0.0436)						
log size			-0.0382**					
			(0.0182)					
log capital raised				-0.0545				
				(0.0334)				
credit standards loose					-0.0623*			
					(0.0353)			
credit standards tight					0.0495			
					(0.0435)			
log TED spread						-0.0810**		
						(0.0313)		
recession 1990/91							0.306***	
							(0.0720)	
recession 2001							0.272***	
							(0.0597)	
recession 2008/09							0.0225	
							(0.0392)	
credit spread								0.0805**
								(0.0310)
mezzanine X PME_{t-1}	0.0380	-0.0215	0.0282	-0.186	0.0971	0.0220	0.0453	0.0964
	(0.205)	(0.209)	(0.205)	(0.127)	(0.209)	(0.201)	(0.205)	(0.184)
direct lending X PME_{t-1}	0.494***	0.477***	0.535***	0.507***	0.475***	0.480***	0.495***	0.455***
	(0.105)	(0.117)	(0.120)	(0.119)	(0.0985)	(0.105)	(0.105)	(0.0979)
special situations X PME_{t-1}	0.743***	0.711***	0.718**	0.756***	0.740***	0.659***	0.746***	0.772***
	(0.271)	(0.249)	(0.276)	(0.260)	(0.278)	(0.243)	(0.269)	(0.280)
distressed debt X PME_{t-1}	0.0771	0.0880	0.0296	-0.00882	0.103	0.0199	0.0537	0.146
	(0.111)	(0.121)	(0.119)	(0.118)	(0.105)	(0.113)	(0.114)	(0.104)
venture debt X PME_{t-1}	0.442***	0.442***	0.492***	0.573***	0.583***	0.322*	0.441***	0.433***
	(0.125)	(0.125)	(0.0918)	(0.167)	(0.134)	(0.168)	(0.112)	(0.0874)
mezzanine	0.144***	0.114**	0.378***	0.428***	0.134***	0.439***	0.130***	-0.0743
	(0.0550)	(0.0483)	(0.141)	(0.161)	(0.0463)	(0.123)	(0.0462)	(0.106)
direct lending	0.0298	0.00980	0.256**	0.301*	0.0432**	0.308***	0.0234	-0.185**
	(0.0349)	(0.0256)	(0.115)	(0.172)	(0.0217)	(0.112)	(0.0201)	(0.0817)
special situations	-0.0975	-0.104	0.173	0.172	-0.0996	0.227	-0.105	-0.346**
	(0.112)	(0.112)	(0.168)	(0.200)	(0.124)	(0.176)	(0.117)	(0.151)
distressed debt	0.0964**	0.0798***	0.370***	0.357**	0.0920***	0.396***	0.0819***	-0.132
	(0.0386)	(0.0228)	(0.136)	(0.170)	(0.0223)	(0.123)	(0.0220)	(0.0865)
venture debt	0.00177	-0.0533	0.209**	0.233	-0.00522	0.310**	-0.0106	-0.230**
	(0.0495)	(0.0538)	(0.101)	(0.148)	(0.0311)	(0.124)	(0.0286)	(0.0882)
Year fixed effects	N	N	N	N	N	N	N	N
Observations	184	184	176	171	184	184	184	184
Adjusted R^2	0.246	0.254	0.253	0.290	0.257	0.272	0.272	0.277

Table 10:
Factors affecting PD Fund Performance and Persistence
(Multiple OLS Regressions)

This table shows OLS regressions of current fund performance (PME_{t}) on previous fund performance (PME_{t-1}), interacted with fund types mezzanine, direct lending, special situations, distressed and venture debt funds. PME is expressed in natural logarithms. The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}. It is used as the investment grade (IG) benchmark. Column 1 controls for US focus, a dummy variable indicating whether a PD fund focuses geographically on the US, industry focus, a dummy variable indicating whether a fund invests in one or related industries as opposed to following a diversified, industry agnostic strategy, and fund size, measured in 2001 US dollars. Column 2 controls for credit spread, calculated as the average spread of periods t and (t+1) between the Moody's Seasoned Baa Corporate Bond and the 10-Year Treasury Constant Maturity, data are from the Federal Reserve St. Louis. Moreover, column 2 controls for credit standards, the average changes as reported in the Federal Reserve's Senior Loan Officer Survey (SLOS) of periods t and (t+1). It is indicated as a positive (negative) percentage change of loan officers tightening (loosening) their credit standards and described in Franzoni et al. (2012). Next, the average TED spread of periods t and (t+1), which is the difference between the interest rate on short-term (3 months) US government debt and the interest rate on interbank loans, is included. Also, column 2 controls for the aggregate capital raised, i.e. the amount of capital raised in the vintage year (t) plus the following year (t+1) as reported by Preqin. Column 3 controlls for NBER recessions, a dummy variable taking the value of one if a f und was launched (vintage year) in a recession period as indicated by the National Bureau of Economic Research (NBER). Various specification employing the variables from columns 1 through 4 are then used and shon in columns 5 through 8. Fund type fixed effects are used. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

DV log PME_{IG}	(1) All periods baseline model	(2) All periods fund criteria	(3) All periods credit market conditions	(4) All periods NBER recessions	(5) All periods full model specification col. 2+3+4	(6) Post-2007 full model specification col. 2+3+4	(7) Post-2007 model w. fund citeria and capital raised col. 2+ cap.raised	(8) Post-2007 model w/o recessions specification col. 2+3
US focus		-0.00552			-0.00539	-0.0306	-0.0256	-0.0314
		(0.0412)			(0.0396)	(0.0421)	(0.0404)	(0.0413)
industry focus		0.0481			0.0345	0.0439	0.0455	0.0455
		(0.0458)			(0.0389)	(0.0320)	(0.0314)	(0.0312)
log size		-0.0332*			-0.0204	-0.0187	-0.0239	-0.0179
		(0.0191)			(0.0167)	(0.0186)	(0.0178)	(0.0175)
recession 1990/91				0.306***				
				(0.0720)				
recession 2001				0.272***	0.138			
				(0.0597)	(0.0912)			
recession 2008/09				0.0225	-0.0193	-0.0386		
				(0.0392)	(0.0785)	(0.0949)		
credit spread			0.0868***		0.0877*	0.117		0.0872
			(0.0314)		(0.0501)	(0.0954)		(0.0611)
credit standards loose			-0.0760*		-0.0726	-0.0798*		-0.0871**
			(0.0413)		(0.0495)	(0.0411)		(0.0376)
log TED spread			-0.120***		-0.103**	-0.102*		-0.104**
			(0.0353)		(0.0429)	(0.0528)		(0.0522)
log capital raised			-0.0485		-0.0349	-0.0145	-0.0673*	-0.0145
			(0.0300)		(0.0372)	(0.0536)	(0.0391)	(0.0535)
mezzanine X PME_{t-1}	0.0378	-0.0285	-0.0120	0.0453	-0.0719	-0.0700	-0.109	-0.0738
	(0.204)	(0.208)	(0.129)	(0.205)	(0.153)	(0.147)	(0.149)	(0.147)
direct lending X PME_{t-1}	0.492***	0.520***	0.420***	0.495***	0.398***	0.384***	0.415***	0.389***
	(0.103)	(0.131)	(0.0920)	(0.105)	(0.0970)	(0.108)	(0.108)	(0.107)
special situations X PME_{t-1}	0.736***	0.701***	0.655**	0.746***	0.638**	0.657**	0.753***	0.658**
	(0.263)	(0.267)	(0.256)	(0.269)	(0.267)	(0.284)	(0.265)	(0.281)
distressed debt X PME_{t-1}	0.0773	0.0431	-0.00332	0.0537	-0.00905	0.154**	0.208***	0.154**
	(0.110)	(0.132)	(0.0952)	(0.114)	(0.113)	(0.0767)	(0.0737)	(0.0760)
venture debt X PME_{t-1}	0.442***	0.492***	0.457***	0.441***	0.508***	0.330**	0.355**	0.318**
	(0.125)	(0.0958)	(0.173)	(0.112)	(0.157)	(0.165)	(0.178)	(0.160)
mezzanine	0.138***	0.327**	0.601***	0.130***	0.589**	0.383	0.635***	0.469
	(0.0457)	(0.142)	(0.218)	(0.0462)	(0.274)	(0.343)	(0.217)	(0.313)
direct lending	0.0244	0.214*	0.491**	0.0234	0.477*	0.300	0.534**	0.383
	(0.0196)	(0.117)	(0.224)	(0.0201)	(0.276)	(0.348)	(0.216)	(0.316)
special situations	-0.1000	0.135	0.378	-0.105	0.385	0.190	0.413*	0.277
	(0.113)	(0.169)	(0.267)	(0.117)	(0.315)	(0.344)	(0.242)	(0.322)
distressed debt	0.0905***	0.328**	0.544**	0.0819***	0.553**	0.370	0.614***	0.455
	(0.0207)	(0.136)	(0.226)	(0.0220)	(0.279)	(0.349)	(0.220)	(0.320)
venture debt	-0.00502	0.139	0.450**	-0.0106	0.416	0.283	0.472**	0.365
	(0.0315)	(0.116)	(0.214)	(0.0286)	(0.268)	(0.354)	(0.202)	(0.318)
Year fixed effects	N	N	N	N	N	N	N	N
Observations	184	176	171	184	165	129	129	129
Adjusted R^2	0.250	0.252	0.371	0.272	0.362	0.419	0.405	0.424

Table 11:
Robustness Tests
(HY Benchmark and Sample Overlap)

This table shows OLS regresssions of current fund performance (PME_{it}) on previous fund performance (PME_{it-1}), interacted with fund types mezzanine, direct lending, special situations, distressed and venture debt funds. PME is expressed in natural logarithms. The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}. It is used as the investment grade (IG) benchmark.Used variables are explained in the other tables. Column 2 controls for potential effects of clustering S.E. at the GP level, column 3 for effects when usnig the high yield instead of the investment grade benchmark. «timedist X PME_{t-1}» in column 4 controls for potential effects from investment and time period overlaps as explained in the main paper text. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	**baseline**	**S.E. clustered at GP level**	**using high yield benchmark**	**time overlap**
US focus	-0.0314	-0.0314	-0.0403	-0.0325
	(0.0413)	(0.0429)	(0.0383)	(0.0414)
industry focus	0.0455	0.0455	0.0548*	0.0438
	(0.0312)	(0.0359)	(0.0310)	(0.0318)
log size	-0.0179	-0.0179	-0.0135	-0.0180
	(0.0175)	(0.0169)	(0.0185)	(0.0176)
credit spread	0.0872	0.0872	0.0559	0.0875
	(0.0611)	(0.0532)	(0.0600)	(0.0613)
credit standards loose	-0.0871**	-0.0871**	-0.0870**	-0.0849**
	(0.0376)	(0.0351)	(0.0369)	(0.0372)
log Ted spread	-0.104**	-0.104**	-0.130***	-0.103*
	(0.0522)	(0.0503)	(0.0494)	(0.0526)
log capital raised	-0.0145	-0.0145	-0.0154	-0.0177
	(0.0535)	(0.0407)	(0.0511)	(0.0545)
mezzanine X PME_{t-1}	-0.0738	-0.0738	-0.0602	0.0406
	(0.147)	(0.147)	(0.119)	(0.211)
direct lending X PME_{t-1}	0.389***	0.389***	0.321*	0.419***
	(0.107)	(0.111)	(0.178)	(0.105)
special situations X PME_{t-1}	0.658**	0.658**	0.568**	0.745**
	(0.281)	(0.264)	(0.243)	(0.309)
distressed debt X PME_{t-1}	0.154**	0.154***	0.210**	0.209**
	(0.0760)	(0.0575)	(0.0810)	(0.105)
venture debt X PME_{t-1}	0.318**	0.318*	0.212	0.395**
	(0.160)	(0.163)	(0.308)	(0.177)
mezzanine	0.469	0.469**	0.582*	0.484
	(0.313)	(0.230)	(0.302)	(0.317)
direct lending	0.383	0.383	0.525*	0.402
	(0.316)	(0.233)	(0.306)	(0.321)
special situations	0.277	0.277	0.452	0.290
	(0.322)	(0.247)	(0.311)	(0.325)
distressed debt	0.455	0.455*	0.569*	0.471
	(0.320)	(0.237)	(0.310)	(0.324)
venture debt	0.365	0.365	0.453	0.382
	(0.318)	(0.232)	(0.308)	(0.322)
timedistXpme_previous				-0.0699
				(0.0825)
Year fixed effects	N	N	N	N
Observations	129	129	130	129
Adjusted R^2	0.424	0.424	0.276	0.420

Table 12:
Robustness Tests
(Level of unrealized asets «rvpi»)

This table shows OLS regresssions of current fund performance (PME_{it}) on previous fund performance (PME_{it-1}), interacted with fund types mezzanine, direct lending, special situations, distressed and venture debt funds. PME is expressed in natural logarithms. The Bloomberg Barclays US Corporate Bond Total Return Index Baa is used to calculate PME_{IG}. It is used as the investment grade (IG) benchmark. Columns 1 through 5 condition on different levels of «rvpi», that is the remaining value scaled by paid-in capital. All other variables are defined as previously explained. Vintage year dummies are included where indicated. Robust standard errors are shown in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

VARIABLES	(1) rvpi <50	(2) rvpi <75	(3) rvpi <100	(4) rvpi <125	(5) rvpi <150	(6) rvpi <225
US focus	0.0831*	0.00662	0.0113	-0.0101	-0.00892	-0.00336
	(0.0463)	(0.0402)	(0.0354)	(0.0386)	(0.0380)	(0.0388)
industry focus	-0.0132	-0.000661	0.00131	0.0193	0.0283	0.0333
	(0.0796)	(0.0518)	(0.0439)	(0.0386)	(0.0370)	(0.0374)
log size	-0.0311	-0.00652	-0.00861	-0.00857	-0.00923	-0.0183
	(0.0250)	(0.0198)	(0.0153)	(0.0146)	(0.0139)	(0.0164)
credit spread	0.0986***	0.0855**	0.0812**	0.0812**	0.0817**	0.0846***
	(0.0364)	(0.0344)	(0.0319)	(0.0323)	(0.0321)	(0.0319)
credit standards loose	-0.0582	-0.0635	-0.0569	-0.0759*	-0.0791*	-0.0816*
	(0.0749)	(0.0586)	(0.0470)	(0.0451)	(0.0445)	(0.0446)
log Ted spread	-0.110**	-0.0781**	-0.0856**	-0.109***	-0.112***	-0.115***
	(0.0467)	(0.0365)	(0.0353)	(0.0357)	(0.0358)	(0.0358)
log capital raised	-0.0532	-0.0843**	-0.0840**	-0.0588*	-0.0520*	-0.0471
	(0.0489)	(0.0395)	(0.0329)	(0.0307)	(0.0299)	(0.0301)
mezzanine X PME_{t-1}	0.0816	0.0470	0.0248	0.0107	-0.0136	-0.0602
	(0.210)	(0.167)	(0.137)	(0.137)	(0.136)	(0.150)
direct lending X PME_{t-1}	0.452***	0.475***	0.510***	0.399***	0.388***	0.395***
	(0.167)	(0.125)	(0.117)	(0.107)	(0.102)	(0.0985)
special situations X PME_{t-1}	-1.979***	0.772***	0.655***	0.664**	0.652**	0.635**
	(0.417)	(0.231)	(0.222)	(0.263)	(0.260)	(0.262)
distressed debt X PME_{t-1}	-0.0618	-0.0599	-0.0834	-0.0382	-0.0263	-0.0242
	(0.135)	(0.127)	(0.122)	(0.112)	(0.110)	(0.111)
venture debt X PME_{t-1}	0.565*	0.695**	0.698**	0.548***	0.534***	0.523***
	(0.292)	(0.308)	(0.301)	(0.165)	(0.160)	(0.153)
mezzanine	0.692**	0.632**	0.670***	0.653***	0.637***	0.686***
	(0.288)	(0.271)	(0.245)	(0.232)	(0.229)	(0.234)
direct lending	0.568*	0.533*	0.567**	0.572**	0.549**	0.577**
	(0.307)	(0.283)	(0.251)	(0.236)	(0.233)	(0.234)
special situations	0.258	0.259	0.390	0.465*	0.446	0.486*
	(0.301)	(0.313)	(0.288)	(0.275)	(0.272)	(0.274)
distressed debt	0.643**	0.574**	0.631**	0.632***	0.613**	0.652***
	(0.296)	(0.278)	(0.249)	(0.239)	(0.236)	(0.238)
venture debt	0.504*	0.485*	0.529**	0.514**	0.489**	0.509**
	(0.290)	(0.269)	(0.243)	(0.231)	(0.228)	(0.229)
Year fixed effects	N	N	N	N	N	N
Observations	86	116	139	160	164	165
Adjusted R-squared	0.307	0.321	0.326	0.343	0.356	0.363

11 Figures

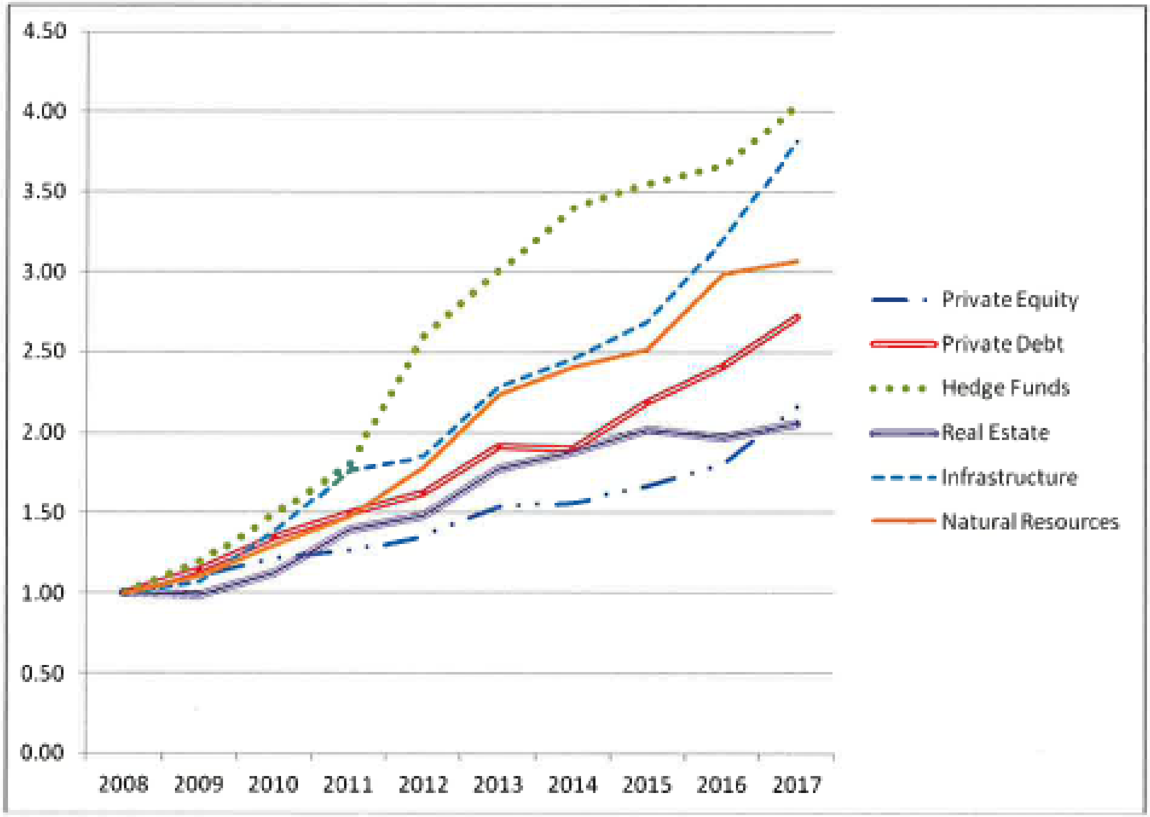

Figure 1: Growth of alternative asset classes from 2008 to 2017, indexed to 2008 (= 1). Source: Preqin (2018).

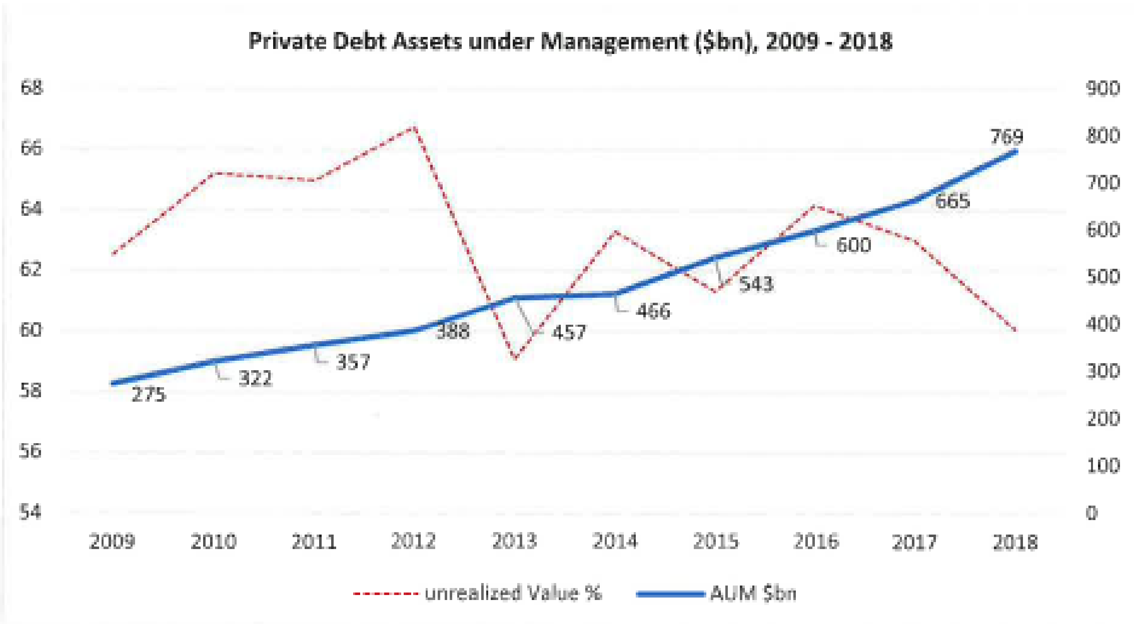

Figure 2: Private Debt assets under management in billion USD from 2009 through 2018. 2009 through 2017 equal to December values, 2018 data as of June. Source: Preqin Pro (2019)

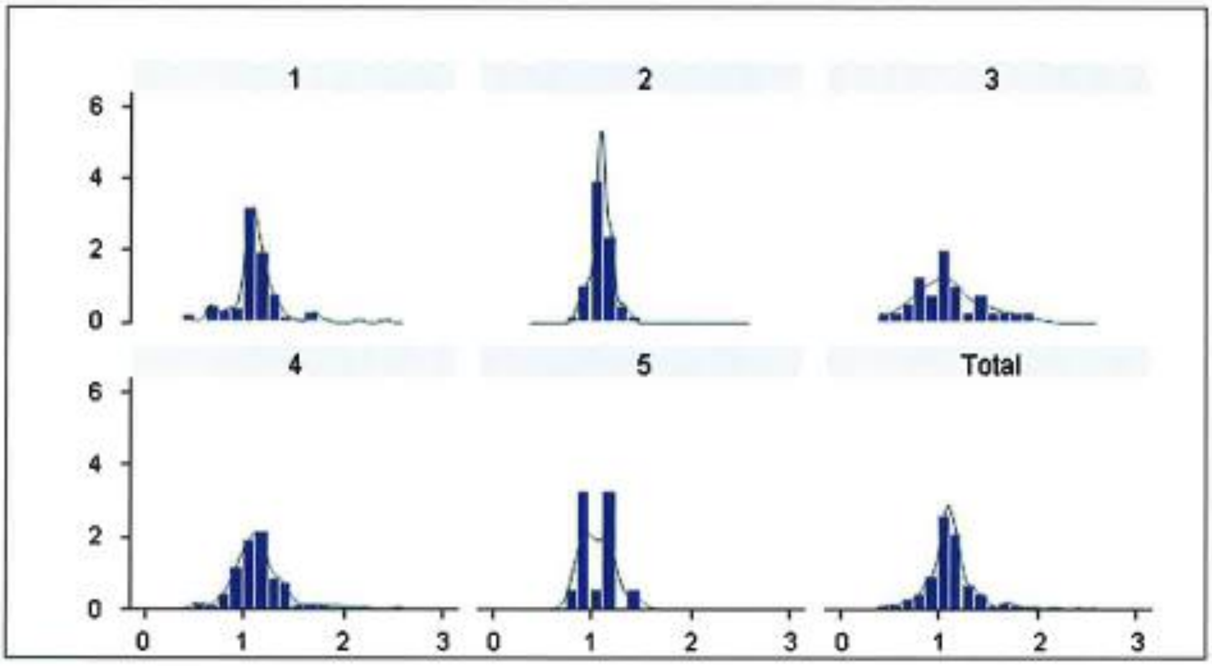

Figure 3: This Figure shows the distribution of the PME net of fees for mezzanine (1), direct lending (2), special situations (3), distressed (4) and venture debt funds (5). The graph represents, for each set of funds and the cross-section of all funds, Gaussian kernel densities.

12 Appendices

Appendix I: Private Debt Fund Types / Strategies

Preqin describes the private capital investment strategies as follows in their Glossary of terms:

Mezzanine	Investments in debt subordinate to the primary debt issuance and senior to equity positions.
Direct lending	The practice of non-bank lenders extending loans to small and medium-sized businesses in return for debt securities rather than equity.
Special situations	Classification covering several areas including distressed and mezzanine, where loan decision or grade is defined by something other than underlying company fundamentals.
Distressed debt	Debt of companies that have filed for bankruptcy or have a significant chance of filing for bankruptcy in the near future.
Venture debt	Debt provided to venture capital-backed companies by a specialized financier to fund working capital or expenses. Venture debt providers combine their loans with warrants or rights to purchase equity to compensate for risk.

Appendix II: NAV write-down of 30% for PD funds beyond their typical liquidation age

Although a subjective exercise, I lean against the expected loss rate of defaulting debt and an estimated probability of default to determine the estimated market value of self-reported NAVs. Studies related to recovery rates for defaulting debt instruments (Chen, 2010; Van de Castle et al., 2000; Davydenko et al., 2012; Altman et al., 2005) and an estimate related to the probability of default based on the findings of Robert and Sufi (2009) provide some empirical support for this adjustment, which is smaller than that proposed by Driessen et al. (2012) or Phalippou and Gottschalg (2009):[145] Self-reported NAVs of funds beyond there typical liquidation age are deemed to be defaulting assets. The value is defined by the loss given default that can be derived from empirical research. Recovery rates for defaulting debt instruments (Chen, 2010; Van de Castle et al., 2000; Davydenko et al., 2012; Altman et al., 2005). Recovery rates that are closest to the nature of PD fund assets are between 37% and 53.5%.[146] Next, the probability of default

[145] They find that market values of nonliquidated PE funds beyond the typical liquidation age are around 30 % of self-reported NAVs. Applying the predictions of Driessen et al. (2012) to self-reported NAVs of PD funds would require a write down for self-reported NAVs of PD funds beyond their typical liquidation age by 70%. Phalippou and Gottschalg (2009) recommend to set the market value of nonliquidated and mature PE funds to zero.

[146] Chen (2010) reports on the average Moody's recovery rates during 1982 to 2008 on defaulted bonds observed roughly 30 days after the default date. It amounts to 41.4%, on average. Van de Castle et al. (2000) analyse recovery rates for a sample of bonds and bank loans between 1987 and 1996 and find an average rate for all debt instruments (bank debt, senior secured debt, senior notes, subordinated debt and junior subordinated debt) of 51.1%. This recovery rate declines with increasing time in default. Davydenko et al. (2012) find average debt recovery rates from 1997 through 2010, equal to the market value of outstanding debt instruments (bonds and bank debt) at the end of the calendar month of default and

related to credit assets held by PD funds beyond their typical liquidation age, which is unknown, needs to be estimated. The probability distribution of unrealized assets to default is unknown. A probability of default of 0.5 is therefore applied. This compares to the cumulative default rate for BBB-rated firms, which amounts to a lower 4% to 5% (see, for example, Kuehn & Schmid, 2014 or Altman et al., 2002). The relatively high probability of default used can be explained from two perspectives. First, a probability of default of 0.5 reflects the diverging approaches used in prior empirical research, which, on the one side, completely depreciate self-reported NAVs (for example in Phalippou & Gottschalg, 2009) or use them, on the other side, as fair market values (Kaplan & Schoar, 2005; Harris et al. (2014a). Second, from a different perspective, Roberts and Sufi (2009) provide support for the application of a relatively high probability of default: They quantify the frequency and importance of private debt renegotiation and show that private credit agreements are renegotiated with a probability of 96%. According to their study, maturity extensions are the outcome in 57% of such renegotiations, these maturity extensions amounting to an average of 766 days or approximately 64% that of the original stated maturity. Such maturity extensions may significantly delay the liquidation of PD funds and can therefore be treated as defaults.

In this study, the loss rate for a sample of bonds and bank loans as observed by Van de Castle et al. (2000) is used. For debt that is in default for more than one year, they find a loss rate of 53.5%. Applying a probability of default of 0.5 and this loss rate leads to an estimated write-off of 26.8%. This loss rate is rounded up to 30%. All self-reported and undistributed NAVs of PD funds beyond their typical liquidation age are depreciated by 30% for the purpose of calculating adjusted performance mesasures.

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expressed as a proportion of the face value of total debt in the amount of 43.5 %. A lower recovery rate in the amount of 37.2% on defaulted debt assets and for an observation period from 1982 through 2001 is shown by Altman et al. (2005).

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The essays collected in this PhD thesis concern the pricing, wealth effects and return of private market debt, which has grown tremendously over the last two decades. Increasingly, companies are seeking flexible terms of private funding rather than capital from public capital markets. The first essay shows how private placement bonds are priced and provides evidence how the use of covenants affects the cost of capital. The second essay examines how the use of restrictive covenants impacts shareholder wealth ex ante and in the context of issuing privately placed bonds. The third essay investigates the risk and returns of private debt funds and their persistence across subsequent funds of a partnership.

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